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Dedication

To My Parents and Sister.

Abstract

Understanding how micro market frictions affect the transmission of macroeconomic risks has been a central research interest in macro-finance. The primary focus of my dissertation contributes to understanding the role of financial and labor market frictions in the impacts of macroeconomic risks on credit and capital allocation, corporate decisions, and asset prices. It also generates a new perspective for policy implementations in credit and labor market regulation.

In Chapter one, I propose a novel channel for the transmission of monetary policy involving shifts in firms' debt structures, the credit substitution channel. Unexpected monetary tightening is associated with a contraction in aggregate corporate bonds but an expansion in business loans. The increase in the loan volume can be explained by the countercyclical demands for loan financing among large unconstrained firms. Using microdata, I demonstrate that large, high-rated firms with low default risk rebalance toward bank loans and away from corporate bonds as the spread of bonds over loans increases. This substitution crowds out banks' lending to small firms, forcing them to raise more equity. I develop a heterogeneous-agent New Keynesian (HANK) model that features debt heterogeneity and credit market frictions to rationalize these empirical findings. In the model, bank loans are senior and safer (collateralized) than defaultable bonds but issued at a greater intermediation cost. Frictions in the flow of liquidity to small firms suggest a role of credit substitution in propagating downturns: small, risky firms disproportionately reduce their investment in response to interest rate hike.

Chapter two is co-authored with Jack Favilukis, Xiaoji Lin, and Xiaofei Zhao. We identify a new channel through which financial intermediary labor leverage affects risk and the real sec-

tor. Financial intermediaries are stressed when their labor share is high. Financial intermediary labor share negatively forecasts growth of aggregate output, investment, and credit lending, and it positively forecasts market excess returns and cost of borrowing. In the cross-section, financially constrained firms connected to banks with higher labor shares borrow less but pay more and have lower investment and earnings growth.

Chapter three is joint work with Xuelin Li, Richard Thakor, and Colin Ward. We build a novel structural model that features a dynamic agency conflict and knowledge spillovers to assess how labor mobility affects intangible investment. Our calibration to US data targets responses of employee turnover and firms' intangible investment to variation in workers' outside option values that are identified by state-level changes in degrees of non-compete enforcement. Counterfactual analysis finds that the current degree of restrictions across states on labor mobility are close to being optimal.

Contents

List of Tables

List of Figures

Chapter 1

Monetary Policy, Debt Structure, and Credit Reallocation

1.1 Introduction

Much of the literature investigating the monetary transmission mechanism predicts that an increase in interest rates is associated with a contraction in the bank loan volume. Several channels are often suggested to explain this association. The first is the interest rate channel, which focuses on the idea that the short rate affects long-term rates through investors' expectations and therefore affects the costs of borrowing and aggregate demand. The second is the bank lending channel, which emphasizes that bank balance sheet conditions matter in order for short rates to affect loan provision. The third is firms' balance sheet channel, which shows that interest rate hikes worsen firms' liquidity conditions by raising interest payments and hence suppress the demand for loans. Note that all these channels predict a reduction in loans after tight money raises credit spreads.

This paper investigates a novel channel for the transmission of monetary policy involving shifts in firms' debt structures, the credit substitution channel. At the aggregate level, interest rate hikes are associated with a contraction in corporate bonds, as expected. However, in contrast to the conventional view, I find a *short-run* (but not transitory) expansion in business loans.[1] At the firm level, I find that large firms substitute loans for bonds. These findings imply that credit substitution is an important channel of monetary policy transmission. In particular, I show that the short-run increase in aggregate business loans is not surprising if we realize that the demand for loan financing by large, safe borrowers (firms) is countercyclical, rising in bad times when the spread between corporate bonds and business loans widens. However, this crowds out loan lending to small firms, forcing them to issue more equity. By shifting the allocation of credit from the small constrained firms to the large unconstrained firms, the credit substitution amplifies the negative effects of tight money and worsens the drop in aggregate investment, as small constrained firms cut down investment more aggressively.

Empirically I start by investigating the relationship between firms' debt borrowing costs, external financing choices, and interest rates using firm-level debt issuance data. Following the interest rate hikes, I find that bond financing becomes relatively more expensive, as bond spreads increase more than loan spreads. Large, unconstrained firms with lower default risk substitute cheaper loans for corporate bonds as the probability of borrowing from banks instead of borrowing from the market increases. Small, low-rated firms that are considered "financially constrained" have a higher propensity to issue new equity. Lastly, the impact of tight money on the debt compositional shift is persistent, even after controlling for the supply side effect. These results hold up to a number of robustness tests.

To understand the driving forces for the empirical findings, I develop a heterogeneous-agent New Keynesian (HANK) model that features debt heterogeneity and credit market frictions. Credit market frictions are characterized by bankruptcy costs, tax benefits, debt and equity issuance costs, and collateral constraints on loan borrowing. The total costs of debt include the exogenous issuance

[1] I use the debt series of the nonfinancial corporate sector from Flow of Funds L.103. The expansion in bank loans at the aggregate level was first documented in Gertler and Gilchrist (1993) over a sample of earlier periods from 1958 to 1993. They use the federal funds rate minus the 10-year government bond rate FF-GB10 as an indicator of monetary policy, and they show a positive cross correlation between FF-GB10 and the growth rate of bank loans around periods of tight money.

costs and the endogenous interest rates charged by the lenders. In the model, the key difference between loans and bonds is that loans are modeled as senior debt secured by physical capital, and bonds are modeled as riskier defaultable debt. Under the assumption of seniority, loan lenders have lower exposure to interest rate risk, so there is a nonnegative spread between bonds and loans. Firms trade off the lower intermediation (issuance) costs of loans against the lower charged interest rates of bonds. Costly loan issuance leads large firms to avoid using up all the collateral when interest rate is relatively low in order to preserve their borrowing capacity for future economic downturns.

I estimate the model by the Simulated Method of Moments (SMM). The model generates steady-state cross-sectional implications for a firm's choice of debt composition, which depends on a firm's default risk. In the model, firms prefer debt to equity financing because of the tax benefit. The credit spread is close to zero for large firms with low default risks, and therefore, they choose to have only bond financing to avoid high loan intermediation costs. Note that for each unit of debt, firms are charged a higher interest rate as they choose a higher bond share, but a lower intermediation cost. Therefore, firms with a median degree of default risk choose an optimal bond share such that they are indifferent between loan and bond financing. The cost of taking bonds exceeds the cost of taking loans for small firms with high default risk. They choose to have a mix of loan and equity financing to avoid high-interest rates, and they exhaust all collateral before going to the equity market.

The economic mechanism emphasizes that firms' preserved debt financing flexibility is an important determinant of firms' adjustments in financing and investment to interest rate risk. The dynamic effects of monetary policy are evaluated by the perfect foresight transition dynamics of positive innovation to the Taylor rule. The shock raises the nominal interest rate and also lowers the inflation rate because of sticky prices, elevating the real rate. Aggregate demand drops in response to the interest rate hike, which leads to a lower output price. These dampen investment demand through both cash flow and discount rate channels. Lower output price, higher credit spreads and higher real debt payment reduce firms' cash flow. The lower cash flow and the higher default risk raise the total expected loss. The credit spread between bonds and loans increases as senior loan lenders have a lower level of risk exposure. Investment adjustment is slow and costly, which generates a demand for external financing despite being more expensive. Ultimately, large firms with unbinding collateral constraint switch from bond issuance toward relatively cheaper loan issuance, while small, constrained firms with high leverage tend to issue more equity. What this implies is that small, bank-dependent firms with a high loan share cut down their investment more aggressively after tight money.

Next, I quantify the redistributive effects of credit substitution. Following a tightening of monetary policy, credit flows away from the bond market to the loan market. Moreover, credit is "misallocated", as there is a rise in the flow of liquidity to large, unconstrained firms but not to small, constrained firms. This suggests that small firms typically suffer a disproportionately greater drop in investment, as in the data. In aggregate, the impulse responses show that a 25 basis point increase in the innovation of the Taylor rule reduces consumption by 0.37%, output by 1.4%, capital by 0.32%, and total debt by 1.55%. In addition, this model quantitatively *reverses* the traditional bank lending channel by generating a short-run expansion in bank loans (5% in five quarters), accompanied by a contraction in corporate bonds (1.9% in five quarters). The frictions in the flow of liquidity to small firms suggest a role of credit substitution in propagating downturns.

In the counterfactual analysis, I show that credit market frictions are quantitatively important to determine the loan-bond tradeoff and evaluate the impact of monetary policy. First, when intermediation costs are set the same for both loans and bonds, firms always prefer loans until they are constrained. This preference creates a counterfactually low bond ratio of 7% in the model, compared to that of 76% in the data. The sensitivity of substitution (the coefficient of the interaction term between monetary shocks and firm size) declined by one-third of that in the baseline model due to less loan financing flexibility. Second, a 10% increase in the production fixed cost raises the default probability and bond spread by 60% and 37%. The economy has a low leverage of 9%, compared to that of 21% in the data sample. The low leverage raises the substitution elasticity by one-half due to more financing flexibility. Third, a one-half reduction in equity issuance costs leads to a 10% drop in the leverage and a 3% drop in the bond share as well as a 20% rise in equity financing. The elasticity of substitution becomes insignificant and close to zero since firms rely more on equity financing.

In summary, this paper points out that the degree of firms' financing flexibility is crucial in understanding the transmission of monetary policy, and it generates important policy implications: to mitigate credit misallocation after tight money, the optimal regulation policy is to provide easier bank credit access to small firms at a lower cost and, at the same time, prevent credit from being overdrawn among large firms.

Related Literature This paper primarily contributes to four strands of literature.

The first strand of literature discusses the monetary policy and bank loan provision. The traditional "bank lending channel" of monetary policy argues that the transmission of monetary policy works through both the asset (loan) and liability (deposit) sides of the bank balance sheet. Early studies include Bernanke and Blinder (1988), Kashyap and Stein (1995), Kashyap and Stein (2000), and Bernanke and Gertler (1995). Recent studies include Drechsler et al. (2017a), Xiao (2020), Wang et al. (2020), Greenwald et al. (2021), Begenau and Stafford (2022), and Supera (2021). The "deposit channel of monetary policy" by Drechsler et al. (2017a) finds that the deposit spread increases as the interest rate goes up. Banks reduce loan lending because the cost of loan provision increases. However, the deposit channel of monetary policy is not well identified, nor does it aggregate. Several recent studies find conflicting evidence. Wang et al. (2020) show that bank market power interacts with capital regulation to *reverse* the effect of monetary policy when the federal funds rate is very low. Specifically, they estimate that, when the federal funds rate is below 0.9%, further cuts in the policy rate can be contractionary. Begenau and Stafford (2022) point out that networked branches and bank concentration are important to consider when examining the deposit channel. They argue that the deposit channel fails to aggregate because of the extreme bank size distribution and the differential behavior of small and large banks. Supera (2021) shows that the shift in banks' funding mix from time deposits (CDs) to savings deposits can explain a long-term decrease in the nominal rate and a decline in banks' supply of business loans, firm investment, and new firm creation. The "credit line channel" proposed in Greenwald et al. (2021) argue that the expansion of bank lending occurs during COVID periods because large firms draw down the credit line of their existing debt, which crowds out banks' provision of term loans to smaller firms, and that exacerbates the fall in aggregate investment. These papers add new insights to the "bank lending channel" literature by emphasizing the importance of bank balance sheets and bank structure in determining loan supply and the transmission of monetary policy. This paper differs from the existing research by proposing a novel, *complementary* channel for the transmission mechanism of monetary policy. It emphasizes that the frictions in the borrowers' balance sheet helps to reconcile the difference between the micro and macro evidence. The *countercyclical demands* for loan financing among large unconstrained firms lead to the *short-run* expansion in aggregate business loans.

Second, this paper speaks to the literature that discusses other channels for the transmission of monetary policy to the real economy and asset prices in a heterogeneous-agent setup. This includes the investment (firm balance sheet) channel,[2] consumption channel,[3] asset prices channel,[4] mortgage refinancing channel, inflation expectations channel, exchange rate channel, and so on.[5] I build on the model developed in Ottonello and Winberry (2020) and contribute to this literature by studying the heterogeneous responses in firms' financing decisions to monetary shocks. This paper differs from the other research in several perspectives. The "floating rate channel" proposed

[2]Papers that study the investment channel include Kashyap et al. (1994), Gertler and Gilchrist (1994), Ippolito et al. (2018), Jeenas (2019), Darmouni et al. (2020), Ottonello and Winberry (2020), Crouzet (2021), and Morlacco and Zeke (2021). They find that firm characteristics such as liquidity, age, default risk, and debt composition drive the differential response in firms' investments.

[3]This includes Kaplan et al. (2018), Auclert (2019), etc.

[4]This includes Bernanke et al. (1999), Bernanke and Gertler (2001), Gilchrist and Leahy (2002), Bhamra et al. (2011), Daniel et al. (2021), and Corhay and Tong (2021).

[5]Dou et al. (2020) provide a critical review of macroeconomic models used for monetary policy at central banks from a finance perspective.

in Ippolito et al. (2018) operates through existing debt, but I focus on the new debt issuance in the primary market. The "bond lending channel" proposed in Darmouni et al. (2020) and the "credit disintermediation" proposed in Crouzet (2021) studies suggest that debt structure is important in explaining heterogeneous investment sensitivities to interest rate risk. I study how firms' balance sheet condition drives the heterogeneous responses in their external financing decisions to interest rate risk as the relative cost of debt changes.[6]

Third, this paper is also related to the large literature that studies the corporate capital and debt structure. Debt structure is a central element in a firm's capital structure. Empirical studies about the cross-sectional debt structure find that asymmetric information, liquidation efficiency, access to the capital market, transaction costs, and firm characteristics such as credit quality, size, leverage, profitability, growth opportunities, and prior financing decisions are important determinants of the corporate debt structure (Houston and James (1996), Johnson (1997), Denis and Mihov (2003), Sufi (2009), Rauh and Sufi (2010), and Colla et al. (2013)). Closely related papers are Adrian et al. (2013), Becker and Ivashina (2014), Li et al. (2019), who study the time variation in the corporate debt structure. They find evidence of substitution between loans and bonds during a financial crisis and when credit conditions tighten and information asymmetry increases. My paper differs in that I show that the substitution between loans and bonds is driven by changes in the relative borrowing costs over the monetary cycle. In terms of the theoretical modeling of debt heterogeneity, the most relevant work is Crouzet (2018), in which he quantifies the transmission of financial shocks through the corporate debt structure on aggregate investment, following the seminal contributions of Diamond (1991), Rajan (1992a), and Bolton and Scharfstein (1996). I contribute to the theoretical modeling by further incorporating debt heterogeneity into a HANK model and provides an algorithm to solve for the nonlinear global solution with occasionally binding constraints.

Fourth, this paper also builds on a large macro-finance literature that studies the (amplification) effect of financial frictions and agency frictions through the lens of dynamic models with endoge-

[6] Schwert (2020) estimates the pricing of bank loans relative to corporate bonds in a novel sample of loans matched with bonds with similar lengths of maturities from the same firm on the same date.

nous investment. An incomplete list includes Gertler and Bernanke (1989), Carlstrom and Fuerst (1997a), Kiyotaki and Moore (1997), Gomes (2001a), Hennessy and Whited (2005), Hennessy and Whited (2007), Rampini and Viswanathan (2013), Rampini and Vishwanathan (2020), Kuehn and Schmid (2014), Li et al. (2016), Alfaro et al. (2018), Belo et al. (2019), and Ai et al. (2020b). Macroeconomic shocks are important determinants of firms' capital structure choices. Financial frictions amplify the effect of exogenous shocks on corporate investment through the changes in asset prices and the external financing premium. Hackbarth et al. (2006) develop a quantitative model of firms' capital structure in which financing decisions vary over the business cycle through its effect on default policies. Jermann and Quadrini (2012a) propose a quantitative theory to show that credit market shocks are necessary to rationalize cyclical external financing choices. Begenau and Salomao (2019) further quantitatively examine the heterogeneous effects of macroeconomic shocks. This paper adds to this literature by allowing for an endogenous debt structure and emphasizing the importance of credit substitution in propagating economic downturns.

The remainder of the paper is organized as follows. Section 1.2 provides the main empirical results, which include data construction, aggregate time series, and firm-level panel analysis. Section 1.3 outlines a dynamic heterogeneous-agent New Keynesian model to interpret the main empirical evidence, where a theoretical characterization of model mechanisms through which monetary policy affects firms' financing decisions is included. Section 1.4 characterizes firms' optimal decisions, details the estimation strategies, and presents model solutions. The quantitative analysis, which includes cross-sectional model validation and firms' differential adjustments, as well as model implications, is included in section 1.5. Section 1.6 discusses the findings, and section 1.7 concludes.

1.2 Empirical Evidence

In this section, I explore how monetary policy affects firms' financing decisions. I first examine aggregate patterns before analyzing the response across a panel of firms.

1.2.1 Data

The sample spans the first quarter of 1990 to the last quarter of 2018. It includes monetary policy shocks, aggregate time-series data from the flow of funds accounts and the Federal Reserve Bank of St. Louis Fed, firm-level accounting variables from Compustat, (syndicated) loan facilities origination from Loan Pricing Corporation's DealScan, as well as corporate bonds issuance from Mergent Fixed Income Securities Database (FISD).

Monetary Policy Shocks

I use the same measurement of unexpected monetary policy shocks as Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016) in the baseline analysis.[7] Specifically, I measure monetary shocks as the changes in the current month's federal funds futures rate in a 30-minute narrow window around Federal Open Market Committee (FOMC) announcements. Daily monetary shock ϵ_t^m is defined as

$$\epsilon_t^m = \tau(t) \times (ffr_{t+\Delta_+} - ffr_{t-\Delta_-}), \tag{1.1}$$

where t is the time of the monetary announcement and ffr_t is the implied fed funds rate from a current-month federal funds futures contract at time t. I focus on a window of $\Delta_- = 10$ minutes before the announcement and $\Delta_+ = 20$ minutes after the announcement. The term $\tau(t)$ is an adjustment for the timing of the announcement within the month.[8] There are 225 high-frequency shocks in my sample. I aggregate the high-frequency shocks to a quarterly frequency following Ottonello and Winberry (2020) by weighting shocks by the amount of time firms have had to react to them. The quarterly monetary shock has a mean of approximately zero and a standard deviation of 9.1 basis points. It has a negative correlation of -0.30 with real GDP growth.[9] Figure 1.1 plots the

[7]They measure monetary shocks using the high-frequency, even-study approach, pioneered by Rudebusch (1998), Kuttner (2001), Cochrane and Piazzesi (2002), and Bernanke and Kuttner (2005). Other approaches include vector autoregression (VAR) studies such as Christiano et al. (1999) and Bernanke et al. (2005) and a narrative approach by Romer and Romer (2004).

[8]This adjustment accounts for the fact that the fed funds futures payout is based on the average effective rate over the month. It is defined as $\tau(t) = \frac{\tau_m^n(t)}{\tau_m^n(t) - \tau_m^d(t)}$, where $\tau_m^d(t)$ denotes the day of meeting in the month and $\tau_m^n(t)$ the number of days in the month.

[9]It contains 37 monetary tightening and 76 monetary easing over the sample.

measured monetary shocks at the daily and quarterly frequency.

[Figure 1.1 and Table 1.1 Here]

Aggregate-level Variables

I obtain the quarterly time series of aggregate U.S. nonfinancial corporate debt from Flow of Funds L.103. Their debt consists primarily of debt securities and loans. Within these two categories, corporate bonds (defined as market debt) account for around 84% of total debt securities, while "depository institution loans not elsewhere classified (defined as bank debt)" and "other loans and advances" together account for around 77% of total loans over the period. The average quarterly changes in corporate bonds and bank loans are 0.93% and -0.08%, respectively. Their correlation with real GDP growth is -0.06 and 0.1, and with the measured monetary shocks, the correlation is -0.12 and 0.15.[10]

Debt Variables

Loan origination data are from DealScan, and corporate bond issuance data are from FISD, which includes information about issuance date, maturity, borrowing amount, and issuer credit rating.[11] Merging debt issuance data with Compustat gives a sample of public firms that have loan financing, bond financing, or both. This sample consists of 25,476 loan facilities, with an average loan amount of $ 431 million, a maturity of 4.16 years, and a spread of 191 basis points. The sample consists of 12,468 corporate bond issuances, with an average quantity of $ 414 million, an average maturity of 11.14 years, and a spread of 183 basis points. Figure 1.2 plots the debt issuance distribution across borrowers' size, split according to Chodorow-Reich et al. (2022)'s

[10] Nonfinancial corporate bonds outstanding in the U.S. grew from approximately $1 trillion in 1990 to approximately $3 trillion in 2008 and to approximately $5.5 trillion at year-end 2018. Similarly, the sum of depository institution loans and other loans together in the U.S. grew from approximately $1.1 trillion in 1990 to approximately $2.2 trillion in 2008, then to approximately $3 trillion at the year-end of 2018.

[11] Wharton Research Data Services (WRDS) has updated the DealScan dataset starting from the summer of 2021. The update is a reorganization of the entire dataset, combining all the information in a single table and changing loan identifiers. The analysis here is based on a vintage version of DealScan, which is now considered the "legacy" version of WRDS. In particular, I use data from the following tables: Facility-Legacy, Package-Legacy, Company-Legacy, Lenders-Legacy, Current Facility Pricing-Legacy, and DealScan-Compustat Linking Database.

classification. The panels on the left represent the new issuance to all Compustat firms, and the panels on the right are the new issuance to public firms with access to both bank loans and corporate bonds. Most of the new debt is issued to large firms. Corporate bonds typically have a longer maturity and larger credit spread relative to bank loans. The difference in maturity between bonds and loans is increasing in borrowers' size, while the difference in the spread is declining in firm size.[12]

Firm-level Variables

I obtain the net equity issuance and loan share from quarterly Compustat. Following Eisfeldt and Muir (2014), the net equity issuance is computed as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC), scaled by lagged total assets. This measure of equity issuance also includes the granting of stock options to employees as a form of compensation. I therefore follow McKeon (2015) to do the adjustment.[13]

Following Crouzet (2021), I define the firm-level loan to be the total of notes payable (NP) and other long-term debt (DLTO) and interpolate missing values of loan if the spells are less than one year.[14] Control variables include firm size, leverage, market-to-book value, tangibility, distance to default (D2D) following Gilchrist and Zakrajšek (2012), an indicator for whether firms pay out dividends, and a dummy for investment grade firms (BBB^- or higher) based on the S&P long-term debt credit rating.

Summary statistics of firm variables can be found in Table 1.1, Panel C. Appendix A.1 contains

[12]Following Chodorow-Reich et al. (2022), I split firms into four groups based on assets: less than \$250 million, \$250–\$999 million, \$1–\$5 billion, and greater than \$5 billion. I refer to all firms with less than \$250 million in assets as SMEs and to firms with over \$1 billion as large firms. The final sample contains 53 firms with between \$50 million and \$250 million in assets, 313 firms with between \$250 million and \$1 billion in assets, 571 firms with between \$1 billion and \$5 billion, and 323 firms with more than \$5 billion in assets.

[13]For each firm quarter, we classify the equity raised by the firm during the quarter as firm initiated if the proceeds represent at least 2% of the firm's end-of-quarter market equity (the equity raised during a quarter is Compustat item SSTKY for Q1 and ΔSSTKY for Q2 to Q4; a firm's end-of-quarter market equity is PRCC × CSHOQ) and scale it by beginning-of-quarter total assets.

[14]Crouzet (2021): NP includes bank acceptances, bank overdrafts, and loans payable. For long-term debt, DLTO includes all revolving credit agreements, as well as all construction and equipment loans. It excludes senior nonconvertible bonds (which are included in debentures, DD), and convertible or subordinate bonds (included in DCVT and DS, respectively). The main drawback is that both NP and DLTO include outstanding commercial paper.

more detailed definitions of these variables and sample construction.

1.2.2 Aggregate-level Dynamics

I estimate the cumulative effects of monetary policy shocks using a Jordà (2005)-style local projection:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \epsilon_t^m + \Gamma_h Controls_{t-1} + \epsilon_{t+h}, \tag{1.2}$$

where $h = 0, 1, ..., 8$ indexes the forecast horizon. Monetary shocks ϵ_t^m are standardized. The dependent variable y is the (log) real debt. The control variables include one year of lagged values of the monetary policy shock and one year of lagged values of the one-quarter change in the respective dependent variable, real GDP growth, inflation rate, unemployment, term spread, SLOOS tightening standards[15], and the forecasts of GDP growth and unemployment. Coefficient β_h measures the cumulative response of corporate debt in quarter $t+h$ to a monetary shock in quarter t. Figure 1.3 reports the estimates of coefficient β_h over quarter h. The effect is large and persistent across all dependent variables. A 25 basis point interest rate hike raises bank loans by 1.8 billions and reduces corporate bonds by 4.8 billions, as shown in panel (a) and (c). The peak of cumulative effects on loan growth is around 1 × 25/9 = 2.78 percentage points in Panel (d), and the peak of cumulative effects on bond growth is around -1.5 × 25/9 = -4.17 percentage points in Panel (b), which remains significant up to five quarters. The initial impact on the flow of total debt is close to zero and remains insignificant for two years.[16]

[Figure 1.3 Here]

[15] The series corresponds to the net percentage of domestic respondents tightening their standard for commercial and industrial (C&I) loans to large and medium-sized firms. A higher value indicates that more banks report tighter credit standards (contraction in bank credit).

[16] The results are robust to various sets of controls and numbers of lags. However, the long-run effect is imprecisely estimated with large standard errors, and therefore, in the rest of the paper, I only focus on the short-run impact of monetary shocks.

1.2.3 Firm-level Analysis

At the aggregate level, the tightening of monetary policy leads to a contraction in corporate bonds and an expansion in bank loans. Analogous to the previous section, I now analyze firms' responses. Using microdata, I estimate the differential effects of monetary policy on debt borrowing costs and firms' external financing decisions at both the extensive and intensive margins.

Debt Financing Decision: Loans vs. Bonds

I first estimate how firms' choices between loans and bonds change in response to monetary shocks, with the following regression:

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\ &+ \delta (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned} \tag{1.3}$$

The variables in $X_{i,t-1}$ are standardized $X_{i,t-1}$ to avoid the results being driven by permanent differences across firms. The variable $Z_{i,t-1}$ is a set of firm characteristics, and the variable Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. α_i is a firm fixed effect, and $\lambda_{s,q}$ is a sector-quarter fixed effect. I also include the interaction between GDP growth and $X_{i,t-1}$ to control for heterogeneous cyclical sensitivities.

My central result establishes a connection between loan and bond substitution and monetary policy at the firm level, conditional on firms' raising new debt financing. By limiting the sample to new debt issuances, I can be certain that firms in the sample have a non-zero demand for credit. Specifically, I keep the firm-quarters that have either a new loan or new bond issuance. The number of firm-quarters in which firms raise both types of debt is rare (3.2% of firm-quarters with new debt) and is likely to be associated with large corporate events such as mergers. Including these observations does not affect our results. This subsample consists of 1,573 firms and 15,287 firm-quarter observations.

However, it is important to recognize this approach's limitations. The sample is restricted to firms with access to both loans and corporate bonds, so it is not representative of the universe of bank borrowers. Despite being a small fraction of the total firms, over half of the new origination are taken by firms in this group and therefore, their financing choices are important for explaining the aggregate dynamics.

Columns (1) to (4) of Table 1.2 report the results at the extensive margin, where the dependent variable is a dummy for debt choices and equals one if a firm chooses new loans and zero if a firm chooses new bonds in quarter t. The positively significant coefficient estimate γ in column (1) is 1.4 percentage points. Compared to a sample average of 58%, this is a 25/9 × 1.4/58 = 6.7% increase in the probability of borrowing from a bank.[17] To avoid the selection issue, I conduct the analysis over loan and bond issuance samples separately, which cover a larger set of firms. On average, firms have a higher (lower) probability of borrowing from bank (issuing bonds) in response to interest rate hikes. The results are included in Table A.2.

Columns (5) to (8) report the results at the intensive margin, where the dependent variable is the change in loan flow measured using Compustat data in quarter t, expressed as a percentage. This is a much larger sample and consists of 8,212 firms and 263,454 firm-quarter observations. Compared to a sample average of 2.39%, the coefficient estimate of 0.275% in column (5) suggests a significant increase, 0.275/2.39 = 11.51%, in the quarterly growth rate of the loan.

[Table 1.2 Here]

The substitution effect is particularly more pronounced for "financially unconstrained" firms, which are large, high-rated firms with lower default risk. The coefficient estimates β in columns (2) to (4) and columns (6) to (8) suggest an economically and statistically significant heterogeneity in the preference for loan financing across firms. A one standard deviation increase in firm size and distance to default further raises the probability of borrowing from bank by 0.7/58 × 25/9 = 3.35%, and 1.8/58 × 25/9 = 8.62%. Only investment-grade firms raise more loans as the interest

[17] Table 1.2 reports the results of a linear probability model. The results of the logistic regression shown in Table A.3 give similar conclusion.

rate rises. The dynamic effects of monetary policy on large, high-rated, and less risky firms are large and persistent, as shown in Figure 1.4.

Equity Financing Decision

I estimate the same regression specification as that in the previous section. This sample consists of 9,072 firms and 418,728 firm-quarter observations.

Columns (1) to (4) of Table 1.3 report the equity financing decisions at the extensive margin, where $y_{i,t}$ is a dummy taking a value of 100 (expressed as a percentage) if the net equity issuance of firm i in quarter t is positive and equals zero otherwise. Columns (5) to (8) report the equity financing decisions at the intensive margin, where the dependent variable is the change in the firm's equity (defined as the difference between total assets and total debt) in quarter t over lagged total assets. On average, firms have a higher probability of issuing new equity following an unanticipated interest rate hike. The coefficient estimate in column (1) is 0.22%. Compared to an average issuance rate of 6.63% and a standard deviation of 25%, this implies that a 25 basis points interest rate hike is associated with a 25/9 × 0.22/6.63 = 9.2% increase in the probability of issuing new equity. The coefficient estimate of 0.124% in column (5) suggests a 25/9 × 0.124/1.08 = 11.5% increase in the quarterly change in equity share. At first glance, this seems to be contradicted by asset price channels of monetary policy, which suggests that a policy-induced increase in the short-term nominal interest rate makes debt instruments more attractive than equities in the eyes of investors, thus causing equity prices to fall. A reasonable explanation is that the higher desire for equity financing among small firms, despite being more costly, leads to an increase in the average net equity issuance, as these firms have a limited debt-borrowing capacity and are usually financially constrained. This can be implied from the negative coefficient estimates of the interaction terms in column (2) and columns (6) to (8). A one standard deviation increase in firm size further reduces the probability of issuing new equity by 25/9 × 0.119/6.63 = 5%, and the equity share by 25/9 × 0.069/1.08=17.7%.

[Table 1.3 Here]

Debt Pricing

Another way to infer a countercyclical demand for loan financing among large, unconstrained firms is to compare the relative prices. I estimate the monetary policy effects on the cost of security j by borrower i at year t following a panel regression:

$$\begin{aligned} Credit\ Spread_{j,i,t} =& \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\ & + \delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,i,t-1} + \Gamma_3' Y_{t-1} + \epsilon_{j,i,t} \end{aligned} \tag{1.4}$$

where loan spread refers to the variable “All-in-drawn”in DealScan, which is the difference between the loan rate and the three-month LIBOR plus an annual fee. The corporate bond spread is measured as the difference between the offering yield and the three-month LIBOR in columns (5) to (8) (maturity-matched interest rate swaps in columns (9) to (12)).[18] Debt characteristics $W_{j,i,t-1}$ include the maturity length and borrowing amount.

The results are summarized in Table 1.4. The coefficient estimate of 0.039 in column (1) indicates that a 25 basis points interest rate hike raises the average loan spread by 3.9 × 25/9 = 10.83 basis points, which is a 5.66% increase compared to the sample average. Column (5) suggests a 18.8 × 25/9 = 52.22 basis points increase in the average bond spread when using the three-month LIBOR as the base rate. This is a 28.54% increase compared to the sample average. The magnitude remains significantly larger, 7.7 × 25/9 = 21.39 basis points, even after adjusting for maturity difference in column (9). The increase in the loan spread is more significant among less risky firms, which is justified by an increase in firm demand for loan financing. However, we do not observe a significant heterogeneity in bond pricing.

[18] Prior literature has found swap rates to be closer to the “true” risk-free rate than Treasury rates, which contain a convenience yield. For instance, see Feldhütter and Lando (2008). Results using the Treasury yield curve are available upon request.

[Table 1.4 Here]

Loans and bonds are different in several dimensions. Compared to corporate bonds, loans on average have collateral, shorter maturities, lower information sensitivity, higher seniority, and a renegotiation benefit.[19] What leads to a lower pass-through from interest rate risk to loan spreads? First, seniority explains why loan lenders have lower risk exposure. Loan lenders have the priority of getting debt payments and hence lower expected loss when firm borrowers declare bankruptcy, as documented by Rauh and Sufi (2010).[20]Loans are safe debt as they are usually negotiable, collateralized, and have less asymmetric information. Second, bond yields, on average, are more sensitive to interest rate changes because of the longer maturity. However, we still see a higher pass-through to bond spreads even after adjusting for maturity differences using swaps as the base rate. To isolate the duration channel, I perform a subsample analysis of new issuance with maturities between 3 and 8 years. By construction, the maturity of loans has a mean of 4.9 years and a median of 5 years, while the maturity of bonds has a mean of 5.5 years and a median of 5 years. The significant estimates in Table A.4 indicate that the heterogeneous pass-through are not completely driven by the duration difference. Third, a stronger lender-borrower relationship is associated with a lower interest rate sensitivity (see Table A.5).

Loans mostly have floating rates, whereas bonds mostly have fixed rates. However, the rate difference itself cannot explain the rising demand for loan financing as floating-rate debt gives higher interest payments when rate goes up, as suggested in the firm's balance sheet channel. This makes loans less attractive. Different from Greenwald et al. (2021) where large firms draw down *existing* credit lines at a *predetermined* rate during COVID periods, I focus on the loan origination in the primary market. Over half of the new issuances are credit lines with a corporate purpose. However, we cannot observe how much credit line the borrowers draw down when issued

[19] In the DealScan sample, loans are mostly taken by firms for corporate purpose instead of being taken by households for real estate purchases. Unlike mortgages, business loans have low prepayment risk and they are less likely used for refinancing. Moreover, we do not observe an increase in the mortgages at the aggregate level.

[20] According to Moody's recovery database for nonfinancial corporations, the median (mean) recovery rate for bank loans was 100% (82%) in the 20 years prior to the financial crisis. In contrast, the median recovery rates for corporate bonds ranged from 67% to 2%, depending on the seniority structure of the particular debt contract (see Figure A.5).

in DealScan.

1.2.4 Summary and Robustness Check

I document the following new facts. 1) Bond financing becomes relatively more expensive as bond spreads increase more than loan spreads. 2) As a result, large, high-rated firms with low default risk substitute bank loans for corporate bonds, and therefore loan borrowing increases. This is consistent with the aggregate evidence. Small, low-rated, risky firms have a higher propensity to issue new equity. These patterns hold at both the extensive and intensive margins. The online Appendix contains several sets of additional empirical results.

The first set of additional results contains two robustness checks of the aggregate analysis. Columns (1) to (4) of Table A.6 decompose the aggregate loans by maturity, showing that monetary shocks have a large and significant impact on short-term loans relative to long-term loans, mostly mortgages. Columns (5) to (8) decompose the measured monetary shocks, suggesting that it is the changes in the short rate ("target" component) rather than the changes in the long rate ("path" component) that drive the results.

The second set of additional results distinguish "financially constrained" firms from "unconstrained" firms using "Whited-Wu" (Whited and Wu (2006a)) and the Size & Age index (Hadlock and Pierce (2010), hereafter, the "HP" index). The results in Table A.7 confirm the robustness of differential adjustments in financing decisions in response to monetary shocks.

The third set of robustness checks discuss the measures of monetary shocks. The high-frequency identification method assumes that no other news is systematically released within the narrow windows around the FOMC announcement. However, the literature on the Fed information effect have called this assumption into question: they posits that the Federal Reserve systematically reveals new information about other economic fundamentals in its meeting announcements, in addition to the pure monetary policy news. Therefore, it is important to differentiate between the two effects. This is not likely to be an issue for two reasons. First, the Fed information effect became dominant after 2007 with the adoption of unconventional monetary policy. The significant results of the pre-crisis (1990-2007) sample analysis included in Table A.8 imply that the results are more likely to be driven by the changes in the short rate. Second, Jarociński and Karadi (2020) exploit the negative and positive co-movement between interest rates and stock prices to disentangle the pure monetary policy effect from the Fed information effect. The correlation between S&P 500 stock return and the pure monetary shocks, information shocks are -0.45 and 0.23, respectively. I employ the pure monetary policy shocks constructed in Jarociński and Karadi (2020) and the results are presented in Figure A.4. Policy news shocks from Nakamura and Steinsson (2018) give similar conclusions, as shown in Table A.9.

Business cycle and monetary cycle are overlapped. The correlation between GDP growth and monetary shocks is reasonably low in this sample. To rule out the business cycle effect, I also control for a set of macroeconomic variables. In addition, Table A.10 shows the asymmetric effects of monetary policy, and it suggests that most of the results are driven by expansionary periods. The effects of monetary policy on firm-level borrowing costs, cash holding, trade credit, dividend payout decision, and excess stock return are presented in Table A.11 and Table A.12.[21]

1.3 Model

To explain the above empirical patterns, I introduce a New Keynesian general equilibrium model with firm heterogeneity and financial frictions to help understand the economic mechanism that drives the empirical results. Firms use internal funds, costly external debt, and equity issuance to finance their production activities. Motivated by the empirical facts, I distinguish loans from bonds by modeling loans as senior collateralized debt but issued at a higher intermediation cost and bonds as riskier defaultable debt. Credit substitution is determined by the changes in the relative prices of these two risky securities and the preserved debt financing flexibility.

[21] Jarociński and Karadi (2020) find that a surprise policy tightening raises interest rates and reduces stock prices, while a complementary positive central bank information shock raises both. The decrease in stock prices and, therefore, stock returns in Table A.12 further confirms this.

Time is discrete and infinite. The model consists of four building blocks: a representative household, a continuum of production firms that make financing and investment decisions, a financial intermediary that prices debt, and a New Keynesian block that consists of a final good producer, a continuum of intermediate retailers, and a monetary authority.

1.3.1 Heterogeneous Firm Producers

Technology and Investment

Firms use physical capital (k) and labor (l) in period t to produce goods (y) using a decreasing returns to scale technology. The production function of firm i at time t is given by

$$y_{i,t} = z_{i,t} k_{i,t}^{\alpha} l_{i,t}^{\nu}, \tag{1.5}$$

where $0 < \alpha + \nu < 1$. Firm-specific productivity $z_{i,t}$ follows a log AR(1) process

$$log(z_{i,t+1}) = \rho_z log(z_{i,t}) + \sigma_z \epsilon_{i,t+1}, \tag{1.6}$$

where $\epsilon_{i,t+1}$ is an $i.i.d.$ standard normal shock that is uncorrelated across all firms in the economy. ρ_z and σ_z are the autocorrelation and conditional volatility of firm-specific productivity, respectively. The production process incurs a fixed cost of c_f if the firm decides to undertake the production.

Firms make investment decisions every period. Physical capital accumulation is given by

$$k_{i,t+1} = (1-\delta) k_{i,t} + i_{i,t}, \tag{1.7}$$

where $i_{i,t}$ represents investment and δ denotes the capital depreciation rate.

When installing new capital or selling old capital, the firm has to incur a quadratic capital adjustment cost with functional form convex adjustment costs $AC(i_{i,t}, k_{i,t})$, given by

$$AC(i_{i,t}, k_{i,t}) = \frac{\phi}{2}\left(\frac{i_{i,t}}{k_{i,t}}\right)^2 k_{i,t}. \tag{1.8}$$

With these capital adjustment costs, I capture in a simple way that capital is illiquid. This form of capital adjustment costs is common in the investment literature, and it is widely used in the corporate finance literature—for example, in Bolton et al. (2013) and Eisfeldt and Muir (2014). Here, I assume an asymmetric adjustment cost: $\phi^+ < \phi^-$: ϕ^+ is the adjustment cost when investment is positive, and ϕ^- is the adjustment cost when investment is negative (disinvestment).

Debt Financing

The firm can borrow via a bank loan, a corporate bond, or both. Every period the firm owner chooses the total amount of debt borrowing $B_{i,t+1}$ and share of bond debt $s_{i,t+1}$. Therefore, the bond amount is $B_{i,t+1}s_{i,t+1}$ and the bank loan amount is $B_{i,t+1}(1-s_{i,t+1})$. The firm owner needs to make the debt payment $(1+c)B_{i,t+1}$ at the beginning of the next period, where c is the proportional coupon for both types of debt that provides a tax advantage. Bonds and loans are different in many dimensions: maturities, seniority, intermediation cost, information sensitivity, floating/fixed rate, and so on. Below I discuss the model assumptions to distinguish bonds from loans.

Assumption 1. (Liquidation and bankruptcy cost)

Liquidation involves deadweight losses. This assumption is common to many models in which the underlying financial friction is limited liability. The creditors receive full payment per unit of debt if the firm does not default. If the firm decides to default on the outstanding debt, the liquidation value is χ fraction of undepreciated capital stock ($0 \le \chi \le 1$): $\chi(1-\delta)k_{i,t+1}$.

Assumption 2. (Debt seniority)

In most cases, bank lenders are more senior than bond lenders. Previous studies have provided empirical support for the assumption.[22] To capture this predetermined seniority structure in the

[22] Loans—either credit lines or term loans—tend to be either fully secured or senior to all other credit obligations,

model, the recovery value per unit of bank loans and corporate bonds is

$$R^l_{i,t+1} = min\left\{\frac{\chi(1-\delta)k_{i,t+1}}{B_{i,t+1}(1-s_{i,t+1})/\Pi_{t+1}}, 1+c\right\}, \tag{1.9}$$

and

$$R^b_{i,t+1} = min\left\{\frac{\chi(1-\delta)k_{i,t+1} - (1+c)B_{i,t+1}(1-s_{i,t+1})/\Pi_{t+1}}{B_{i,t+1}s_{i,t+1}/\Pi_{t+1}}, 1+c\right\}. \tag{1.10}$$

This assumption is crucial to generate lower risk exposure for loan lenders and, therefore, a rise in the credit spread of bonds over loans in response to an interest rate hike.

[Figure A.5 Here]

Assumption 3. (Collateralized loans)

In the model, the collateral constraint a firm faces on loan borrowing is

$$(1+c)B_{i,t+1}(1-s_{i,t+1}) \leq \theta(1-\delta)k_{i,t+1}. \tag{1.11}$$

Here, only θ fraction of undepreciated capital can be used as collateral, which affects the tightness of the collateral constraint and determines the borrowing capacity. I further assume $0 < \theta < \chi$, which means that bank lenders cannot always get full payment during bankruptcy even though the loan is secured. This generates a time-varying loan spread.

Assumption 4. (Loan issuance is more costly)

Debt issuance is costly.[23] For simplicity, I assume that there is a linear issuance cost ξ_0 and ξ_1 per unit of loans and bonds, respectively. The debt issuance cost is higher for an intermediated

whereas bonds tend to be unsecured, subordinated, or both. For instance, Diamond (1993) suggests that the seniority and collateralization of short-term debt can serve as compensation for the monitoring cost of short-term creditors. Rauh and Sufi (2010) document that, in a sample of rated firms, 53.9% of all secured debt consists of credit lines or term loans, and a further 31.8% consists of mortgage and equipment debt. Subordinated debt, on the other hand, entirely comprises (either convertible or nonconvertible) debt. Crouzet (2018) finds that a very large portion of short-term debt (on average, 95%) constitutes loans. To the extent that these loans are extended by banks, they are almost always senior, as discussed in Welch (1997).

[23]Fang (2005) finds that bond issuance in the U.S. has an average underwriting fee of 0.95%. Philippon (2015) estimates the overall intermediation costs in the U.S. financial sector to be approximately 2% between 1870 and 2012.

bank loan: $\xi_0 > \xi_1$, because of costly intermediation.[24] The functional form for debt issuance cost is given by

$$DIC(B_{i,t+1}, s_{i,t+1}) = \xi_0 B_{i,t+1}(1 - s_{i,t+1}) + \xi_1 B_{i,t+1} s_{i,t+1} = \xi_0 B_{i,t+1} + (\xi_1 - \xi_0) B_{i,t+1} s_{i,t+1}, \tag{1.12}$$

Assumption 5. (Short-term debt)

On average, bonds have a longer maturity than loans. Both loans and bonds take the form of a one-period contract in the model for simplicity. This assumption can be relaxed to short-term loans and long-term bonds to include the duration channel.

Equity Financing

Taxable corporate profits are equal to output less capital depreciation and interest expenses: $y_{i,t} - \delta k_{i,t} - cB_{i,t}/\Pi_t$. A firm's internal funds in period t is defined as after-tax profit (output minus labor expense) plus the value of undepreciated capital and the tax benefit net of debt payment and fixed production cost:

$$\begin{aligned} n_{i,t} = \max_{l_{i,t}} \; & (1-\tau)(p_t z_{i,t} k_{i,t}^{\alpha} l_{i,t}^{\nu} - w_t l_{i,t}) + \tau(\delta k_{i,t} + cB_{i,t}/\Pi_t) \\ & + (1-\delta) k_{i,t} - c_f - (1+c) B_{i,t}/\Pi_t \\ & = (1-\tau) w_t^{\frac{\nu}{\nu-1}} \left[\nu^{\frac{\nu}{1-\nu}} - \nu^{\frac{1}{1-\nu}} \right] \left(p_t z_{i,t} k_{i,t}^{\alpha} \right)^{\frac{1}{1-\nu}} + \tau(\delta k_{i,t} + cB_{i,t}/\Pi_t) \\ & + (1-\delta) k_{i,t} - c_f - (1+c) B_{i,t}/\Pi_t. \end{aligned} \tag{1.13}$$

[24] Bank borrowing requires active relationship management (firm owners need to share private information with their bank lenders to verify loan covenants), and banks do monitoring to overcome the problem of asymmetric information between lenders and borrowers. This assumption can be relaxed to allow procyclical and heterogeneous issuance costs: the process of loan intermediation is more costly for riskier firms. The average intermediation costs are higher in bad times.

It follows that a firm's budget constraint can be written as

$$d_{i,t}+k_{i,t+1}=n_{i,t}+Q^{l}_{i,t}B_{i,t+1}(1-s_{i,t+1})(1+c)+Q^{b}_{i,t}B_{i,t+1}s_{i,t+1}-DIC(B_{i,t+1},s_{i,t+1})-AC(i_{i,t},k_{i,t}), \tag{1.14}$$

in which τ is the corporate tax and $d_{i,t}$ is the dividend payout. Firms do not incur costs when paying dividends or repurchasing shares. Besides internal funds and debt, firms can also finance their investment via equity issuance, modeled as a negative dividend. External equity issuance is costly and consists of a fixed and proportional cost: $EIC(d_{i,t}) = (\lambda_0+\lambda_1|d_{i,t}|)\mathbb{1}(d_{i,t}<0)$. The effective cash flow distributed to shareholders is given by

$$d_{i,t}-EIC(d_{i,t}). \tag{1.15}$$

New Entrants

Every period, new entrants enter the economy with initial capital k_0 from households and have zero debt. The mass of new entrants is equal to the mass of firms that exit the economy so that the total mass of production firms is fixed in each period. Each of these new entrants draws idiosyncratic productivity $z_{i,t}$ from the time-invariant distribution $\mu^{ent}(z)\sim logN\left(-m\frac{\sigma}{\sqrt{1-\rho^2}},\frac{\sigma}{\sqrt{1-\rho^2}}\right)$. They then proceed as incumbent firms.

Timing

The timing of events within a period is as follows:

(i) **Default decision** All firms (include the new entrants) enter into each period with productivity, capital, and total debt $(z_{i,t},k_{i,t},B_{i,t})$. At the beginning of period t, the firm decides whether to continue or default: $D_{i,t}$ based on firm equity value $V_{i,t}$:

$$\begin{cases} D_{i,t} = 0 & \text{if } V_{i,t} \geq 0 \\ D_{i,t} = 1 & \text{if } V_{i,t} < 0. \end{cases}$$

If the firm defaults, it immediately and permanently exits the economy. In the event of default, lenders recover a fraction of the firm's undepreciated capital stock $\chi(1-\delta)k_{i,t}$ as debt payment. To continue, the firm must pay back the face value of outstanding debt: $(1+c)B_{i,t}$ and pay a fixed operating cost c_f.

(ii) **Production** Continuing firms produce. They hire labor $l_{i,t}$ from a competitive labor market with wage rate w_t. The firm's net worth in period t is defined above.

(iii) **Investment** Firms have three sources for financing their investment $k_{i,t+1}$. First, firms can use internal financing by lowering dividend payments. Second, firms can issue corporate debt—both loans and bonds—which incur an issuance and bankruptcy cost. Lenders offer a price schedule $Q^l(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1})$ for loans and $Q^b(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1})$ for bonds. Third, firms can issue equity with a variable and fixed cost.

Recursive Formulation

A firm's optimization problem can be written recursively. Conditional on continuing, firms make decisions on labor hiring, investment, and borrowing: (l, k', B', s'). The state variables of a firm are productivity, capital, and total debt (z, k, B). Conditional on continuing, the equity value $V_t(z, k, B)$

solves the following Bellman equation:

$$
\begin{aligned}
V_t(z,k,B) &= \max_{l,k',B',s'} d - EIC(d) + \mathbb{E}_t[\Lambda_{t,t+1} \max_{D'(z',k',B')\in\{0,1\}} V_{t+1}(z',k',B')] \\
s.t \quad n &= (1-\tau)(p_t z k^{\alpha} l^{\nu} - w_t l) + (1-\delta)k + \tau(\delta k + cB/\Pi_t) - c_f - (1+c)B/\Pi_t \\
d + k' &= n + Q^l_{i,t} B'(1-s') + Q^b_{i,t} B' s' - DIC(B',s') - AC(i,k) \\
B'(1-s')(1+c) &\leq \theta(1-\delta)k' \\
k' &= (1-\delta)k + i,
\end{aligned}
$$

where $D'_{t+1}(z',k',B')$ is an indicator variable taking the value of one when the firm defaults and $0 \leq s' \leq 1$. $\Lambda_{t,t+1} = \beta \frac{U'(C_{t+1})}{U'(C_t)}$ is the discount factor that equals β at the steady state. The capital adjustment cost $AC(i,k)$, debt issuance cost $DIC(B',s')$, and equity issuance cost $EIC(d)$ are defined in the above section.

1.3.2 Financial Intermediary

The financial intermediary takes the household's savings deposit and lends it to firm producers in the form of risky debt. The debt contract specifies the debt prices from intermediary's break-even condition at the steady state:[25]

$$
Q^j_t(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1}) = \mathbb{E}_t\left[\frac{\Lambda_{t,t+1}}{\Pi_{t+1}}\Big((1-D_{i,t+1})(1+c) + D_{i,t+1}\max\{R^j_{i,t+1}, 0\}\Big)\right], \tag{1.16}
$$

where $j = l, b$. The yield on the defaultable debt is defined as $\frac{1+c}{Q^j_{i,t}}$. Therefore, the yield spread between bonds and loans can be computed as

$$
\frac{1+c}{Q^b_{i,t}} - \frac{1+c}{Q^l_{i,t}}, \tag{1.17}
$$

[25]Frictions in the intermediary are not discussed in the model for computation simplicity. Differences between bond and loan lenders are reflected in the structure of debt contract. The inclusion of supply-side frictions will further amply the quantitative results.

The properties of debt prices are discussed in the next section.

1.3.3 Household

There is a representative household with preferences over consumption C_t and labor supply L_t represented by the expected utility function

$$\mathbb{E}_0 \sum_t^{\infty} \beta^t (logC_t - \Psi L_t),$$

where β is the discount factor and Ψ controls for the disutility of labor supply. The household owns all firms in the economy so they earn a profit share from the producers. The household can also save on risk-free bonds. The consumption-saving decision gives the Euler equation that links the discount factor and the nominal interest rate: $\Lambda_{t,t+1} = \frac{1}{R_t^{nom}/\Pi_{t+1}}$.

1.3.4 The New Keynesian Block

The New Keynesian block of the model consists of a final good producer, intermediate retailers who introduce price rigidity, and a monetary authority who sets the interest rate rule. It generates 1) a New Keynesian Phillips curve relating nominal variables to the real economy and 2) a Taylor rule, which links the monetary policy shock and inflation to the nominal interest rate.

Final good producer There is a representative final good producer who produces the final good Y_t using intermediate goods from all retailers with the production function:

$$Y_t = \left(\int \tilde{y}_{i,t}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}},$$

where γ is the elasticity of substitution between intermediate goods. The final good producer's profit maximization problem gives the demand curve $\tilde{y}_{i,t} = \left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma} Y_t$ where the price index is $P_t = \left(\tilde{p}_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}$. The final good serves as the numeraire in the model.

Intermediate retailers There is a fixed mass of retailers $i \in (0,1)$. Each retailer i produces a differentiated variety $\tilde{y}_{i,t}$ using the undifferentiated good $y_{i,t}$ from heterogeneous firm producers as its only input: $\tilde{y}_{i,t} = y_{i,t}$.

The retailers are monopolistic competitors who set their prices $\tilde{p}_{i,t}$ subject to the demand curve generated by the final good producer and the wholesale price of the input P_t. Retailers pay a quadratic menu cost in terms of final good $\frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$ in order to adjust their prices, as in Rotemberg (1982), where Y_t is the final good. The resulting price stickiness comes from the price-setting decisions made by retailers maximizing profits.

$$\pi_{i,t} = (\tilde{p}_{i,t} - p_t)\tilde{y}_{i,t} - \frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t,$$

Proposition 1. *The retailer's profit maximization gives the following* ***New Keynesian Phillips curve****:*

$$log\Pi_t = \frac{\gamma - 1}{\psi} log\frac{p_t}{p*} + \beta\mathbb{E}_t log\Pi_{t+1}, \tag{1.18}$$

where $p* = \frac{\gamma-1}{\gamma}$ *is the steady-state wholesale price, or in other words, the marginal cost for retailer firms.*

The Phillips curve links the New Keynesian block to the production block through the real wholesale price $p*$ for production firms. If the expectation of future inflation is unchanged, when aggregate demand for the final good Y_t increases, retailers must increase the production of their differentiated goods because of the nominal rigidity. This in turn increases demand for the production goods $y_{i,t}$, which raises the real wholesale price p_t and generates inflation through the Phillips curve.[26]

[26]The aggregate demand channel helps to match the credit spread of bonds over loans in equilibrium as a drop in the real wholesale price p_t further reduces firm producers' cash flow.

Proposition 2. ***Inflation dynamics*** *follows*[27]

$$\Pi_t = exp\left(\frac{1}{\psi_\pi}\left[log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right) - \epsilon_t^m\right]\right). \tag{1.19}$$

Monetary authority The monetary authority sets the nominal risk-free R_t^{nom} according to the log version of a Taylor rule:

$$log(R_t^{nom}) = log\frac{1}{\beta} + \psi_\pi log\Pi_t + \epsilon_t^m, \tag{1.20}$$

where $\epsilon_t^m \sim N(0, \sigma_m^2)$, Π_t is gross inflation in the final good price, ψ_π is the weight on inflation in the reaction function, and ϵ_t^m is the monetary policy shock.

1.3.5 Model Equilibrium

The steady-state equilibrium for this economy is given by a set of value functions $V_t(z_{i,t}, k_{i,t}, B_{i,t})$; decision rules $\{k_{i,t+1}, B_{i,t+1}, s_{i,t+1}, l_{i,t}\}$ for capital, total debt, bond share, and labor hiring; a default policy $D_{t+1}(z_{i,t+1}, k_{i,t+1}, B_{i,t+1})$ and a measure of firms $\mu_t(z_t, k_t, B_t)$; a loan and bond price schedule $Q_{i,t}^j(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1})$; and a set of prices w_t for the wage rate, p_t for the firm output price and $\Lambda_{t,t+1}$ for the discount factor, such that

(i) Given prices, the policy functions $\{k_{i,t+1}, B_{i,t+1}, s_{i,t+1}, l_{i,t}\}$, default policy $D_{t+1}(z_{i,t+1}, k_{i,t+1}, B_{i,t+1})$, and the value function $V_t(z_{i,t}, k_{i,t}, B_{i,t})$ solve the firm's optimization problem;

(ii) Given prices, the household optimizes;

(iii) Lenders price default risk competitively;

(iv) The stationary distribution of firms is consistent with decision rules;

(v) The consumption good market, labor market, and corporate debt markets all clear.

[27]Following an interest rate hike, wholesale price p_t declines and deflation takes place. It amplifies the short rate effects quantitatively as deflation raises the real debt payment and thus lowers firm cash flow.

1.4 Model Solution

1.4.1 Optimal Decisions

In this section, I explore a firm's optimal decisions and their related properties.

Optimal Capital Structure

Proposition 3. *The price of a risky bond is lower than a senior collateralized loan as compensation for higher expected bankruptcy loss: $Q^b_{i,t}(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1}) \le Q^l_{i,t}(z_{i,t}, k_{i,t+1}, B_{i,t+1}, s_{i,t+1})$. This can be easily inferred from the repayment policy.*

Proposition 4. *The prices of debt securities are increasing in capital investment and decreasing in the borrowing of risky debt: $\frac{Q^j_{i,t}}{k_{i,t+1}} > 0$, $\frac{Q^j_{i,t}}{B_{i,t+1}} < 0$ and $\frac{Q^j_{i,t}}{s_{i,t+1}} < 0$, where $j = l, b$.*

Higher current investment leads to higher output and more internal funds, which reduces the firm's default probability and expected bankruptcy loss in the next period. Carrying more (riskier) debt that are less valuable today leads to higher future debt payment. It raises the default probability and expected bankruptcy loss.

Proposition 5. *Let η_t be the Lagrangian multiplier associated with the collateral constraint. The first-order condition with respect to $k_{i,t+1}$ and $B_{i,t+1}$ are, respectively,*

$$
\begin{aligned}
&\left(1+\lambda_1 \mathbb{1}(d_{i,t}<0)\right)\left(1+\frac{\partial AC_{i,t}}{\partial k_{i,t+1}}-\frac{\partial Q^b_{i,t}}{\partial k_{i,t+1}}B_{i,t+1}s_{i,t+1}-\frac{\partial Q^l_{i,t}}{\partial k_{i,t+1}}B_{i,t+1}(1-s_{i,t+1})\right)-\eta_t\theta(1-\delta)\\
=&\mathbb{E}_t\left[\Lambda_{t,t+1}\left(\alpha(1-\tau)p_{t+1}z_{i,t+1}k^{\alpha-1}_{i,t+1}l^{\nu}_{i,t+1}+\tau\delta+(1-\delta)-\frac{\partial AC_{i,t+1}}{\partial k_{i,t+1}}\right)\left(1+\lambda_1\mathbb{1}(d_{i,t+1}<0)\right)\left(1-D_{i,t+1}\right)\right],
\end{aligned}
\tag{1.21}
$$

and

$$\left(1+\lambda_1 \mathbb{1}(d_{i,t}<0)\right)\left(\frac{\partial Q^l_{i,t}}{\partial B_{i,t+1}} B_{i,t+1}(1-s_{i,t+1}) + Q^l_{i,t}(1-s_{i,t+1}) + \frac{\partial Q^b_{i,t}}{\partial B_{i,t+1}} B_{i,t+1} s_{i,t+1} + Q^b_{i,t} s_{i,t+1} \right.$$
$$\left. - (\xi_0 + (\xi_1 - \xi_0) s_{i,t+1})\right) - \eta_t (1-s_{i,t+1})(1+c) = \mathbb{E}_t \left[\Lambda_{t,t+1}\left(1+\lambda_1 \mathbb{1}(d_{i,t+1}<0)\right)\left(\frac{1+c-\tau c}{\Pi_{t+1}}\right)(1-D_{i,t+1})\right]. \tag{1.22}$$

The left-hand side of the equation (1.21) is the marginal cost of investment, and the right-hand side is the marginal benefit. The marginal capital adjustment cost $\left(1+\frac{\partial AC_{i,t}}{\partial k_{i,t+1}}\right)$ is augmented by the marginal cost of issuance $(1+\lambda_1 \mathbb{1}(d_{i,t}<0))$. More important, one additional unit of capital $k_{i,t+1}$ will reduce the marginal cost through (1) relaxing the collateral constraint $-\eta_t \theta(1-\delta)$ and (2) the price effect $\frac{\partial Q^j_{i,t}}{\partial k_{i,t+1}}$: more investment leads to higher output in the next period and, therefore, a lower default probability. The next-period marginal benefit of this additional unit of capital depends on the marginal benefit of investing in real technology and the reduction in the future marginal cost of equity issuance and default probability due to an increase in retained earnings.

Equation (1.22) equates the marginal cost of one additional unit of debt with its marginal benefit. The marginal benefit of debt financing is the tax benefit, while the marginal cost is the weighted average of debt borrowing costs (including their issuance costs $\xi_0 + (\xi_1 - \xi_0)s_{i,t+1}$), interest rates charged by the lenders, and constraint risk $\eta_t(1-s_{i,t+1})(1+c)$. The marginal cost is increasing in the marginal issuance cost of equity because firms may need to take on costly external equity financing to repay the debt due next period. The above two equations pin down a firm's optimal capital structure.

Optimal Debt Structure

Firms trade off between the higher intermediation cost of loans and the higher charged interest rate of bonds when choosing the optimal debt composition. Within each period, given $(z_{i,t}, k_{i,t+1}, B_{i,t+1})$, firms choose their optimal debt composition $s_{i,t+1}(z_{i,t}, k_{i,t+1}, B_{i,t+1})$ to maximize the total debt value, subject to a collateral constraint on loan borrowing. The objective function is

$$
\begin{aligned}
F = & \max_{s_{i,t+1}} \quad Q^l_{i,t} B_{i,t+1}(1-s_{i,t+1}) + Q^b_{i,t} B_{i,t+1} s_{i,t+1} - DIC(B_{i,t+1}, s_{i,t+1}), \\
& s.t \;\; 1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)} \leq s_{i,t+1} \leq 1.
\end{aligned}
\tag{1.23}
$$

The lower bound of $s_{i,t+1}$ comes from the collateral constraint. The first-order condition with respect to the optimal bond share $s_{i,t+1}$ is

$$
\frac{\partial F}{\partial s_{i,t+1}} = \xi_0 - \xi_1 + \left(Q^b_{i,t} - Q^l_{i,t}\right) + \frac{\partial Q^b_{i,t}}{\partial s_{i,t+1}} s_{i,t+1} - \frac{\partial Q^l_{i,t}}{\partial s_{i,t+1}} s_{i,t+1}. \tag{1.24}
$$

Let $s^\star_{i,t+1}$ denote the optimal bond share and $\hat{s}_{t+1}$ be the solution for equation (1.24).

Proposition 6. *For* $\forall\ (z_{i,t}, k_{i,t+1}, B_{i,t+1})$ *such that* $Q^b_{i,t} \simeq Q^l_{i,t}$ *for* $\forall s_{i,t+1}$*:* $s^*_{i,t+1} = 1$

i.e, when firms are charged the similar rates from bond and loan lenders, they choose bond debt only.

Proof. See Appendix A.2. □

Proposition 7. *For* $\forall\ (z_{i,t}, k_{i,t+1}, B_{i,t+1})$ *such that* $Q^b_{i,t} < Q^l_{i,t}$

1. $s^*_{i,t+1} = \hat{s}_{t+1} \leq 1$, *if* $1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)} < \hat{s}_{t+1}$, *i.e, firms are financially unconstrained,*
2. $s^*_{i,t+1} = 1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)}$, *if* $1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)} \geq \hat{s}_{t+1}$, *i.e, firms are financially constrained,*

where $\hat{s}_{t+1} = \frac{(\xi_0-\xi_1)+(Q^b_{i,t}-Q^l_{i,t})}{\frac{\partial Q^l_{i,t}}{\partial \hat{s}_{i,t+1}} - \frac{\partial Q^b_{i,t}}{\partial \hat{s}_{i,t+1}}}$ *such that* $\frac{\partial F}{\partial s_{i,t+1}}|_{s_{i,t+1}=\hat{s}_{t+1}} = 0$.

That is, when there is a certain degree of spread between bonds and loans: $\frac{1+c}{Q^b_{i,t}} - \frac{1+c}{Q^l_{i,t}} > 0$, *they choose debt mix financing. The optimal debt composition is*

$$
s^*_{i,t+1} = \frac{(\xi_0 - \xi_1) + (Q^b_{i,t} - Q^l_{i,t})}{\frac{\partial Q^l_{i,t}}{\partial s^*_{i,t+1}} - \frac{\partial Q^b_{i,t}}{\partial s^*_{i,t+1}}},
$$

for financially unconstrained firms (i.e, the collateral constraint is not binding) and

$$
s^*_{i,t+1} = 1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)},
$$

for financially constrained firms.

Proof. See Appendix A.2. □

Firms' leverage $\frac{B_{i,t+1}}{k_{i,t+1}}$ and default risk together determine the cross-sectional distribution of debt composition in the steady-state equilibrium. The model predicts that firms prefer debt to equity financing because of the tax benefit and lower issuance costs. Suppose the corporation would like to raise additional funds for investment beyond internal funds in the steady state; in this case, it will use debt first. The total costs of debt include exogenous issuance costs and endogenous interest rates charged by the lenders. In the cross-section, large firms with little default risk always prefer bond financing to avoid costly bank intermediation, as bonds and loans are charged similar interest rates: $\frac{1+c}{Q^b_{i,t}} - \frac{1+c}{Q^l_{i,t}} \simeq 0$ (see Proposition 6). They also have an incentive to keep financing flexibility for future economic downturns and stay away from binding constraints because of costly debt issuance. As they take on more debt, they incur a higher interest payment, which lowers retained earnings and leads to higher default risk and a higher credit spread. Firms with a median degree of default risk choose a mix of bonds and loans. Note that for each unit of debt, the higher the bond share, the higher the endogenous interest rate charged but the lower the exogenous intermediation cost paid. The optimal bond share they choose equals the cost of loans to the cost of bonds before they reach the borrowing limit (see Proposition 7). After that, firms seek bond financing again if they need extra funds. Small firms with high default risk resort to equity financing when the credit spread is high enough. They switch to equity financing after they run out of collateral.

1.4.2 Calibration and Estimation

I study the model solutions and perform a quantitative analysis by means of calibration and estimation. I start with an explanation of the quarterly calibration and estimation, followed by discussions on model mechanisms and policy functions. I solve for the steady-state equilibrium via a value function iteration and do transition dynamics following a one-time interest rate shock. Details on the numerical algorithm are included in Appendix A.3. The quarterly parameter predetermination (calibration) is summarized in Table 1.5, and the parameter estimation is summarized in Table 1.7. I take parameter values reported in the literature whenever possible and choose the rest of them to match the data moments from the empirical sample. Estimation of the parameters is achieved by the simulated method of moments (SMM), which minimizes a distance criterion between key moments from the real data and the simulated data. The model is computationally intensive, and therefore only five parameters are estimated, while the remaining parameters are predetermined. Predetermined parameters can be divided into four groups: incumbent (technology, financing, and productivity), new entrant, household's preference, and New Keynesian block.

Calibration

Firm's technology The first block of the table reports the production parameters of the model. I set the capital share $\alpha = 0.21$ to match the average profits, and the labor share $\nu = 0.64$, which gives $\frac{\alpha}{1-\nu} = 0.58$, in line with the evidence in Cooper and Ejarque (2003) and close to the estimate in Li et al. (2016). This implies a total return to scale of 85%. Capital depreciates at a rate $\delta = 10\%$ per year, which is a standard assumption. The capital adjustment parameters ϕ^+ and ϕ^- are calibrated to match the cross-sectional dispersion of investment.

Firm's productivity Persistence ρ_z and conditional volatility σ_z of the idiosyncratic productivity shock are calibrated to match the autocorrelation and cross-sectional dispersion of profitability and leverage.

Firm's financing Firms can issue debt and equity. I set the effective corporate tax rate τ to be 0.3, the same as in Nikolov and Whited (2014). Upon default, bond investors can recover part of the asset value. The senior unsecured bond recovery rate from 1983 to 2017 was 37.74%, as reported in Exhibit 7 of Moody's report. I set the recovery rate to $\chi = 0.38$. The collateral parameter θ is set to be 0.5, following Li et al. (2016).

New entrants (firm life cycle) I assume that new entrants draw their productivity from distribution $N(-m\frac{\sigma^2}{\sqrt{1-\rho^2}}, \frac{\sigma^2}{\sqrt{1-\rho^2}})$, and with an initial level of capital k_0 to be 1 and zero debt. The number of new entrants is chosen to have a constant measure of firms. I set the mean shift of entrants' productivity to $m = 1.2$. k_0, which is set to match the employment share of young firms.

Household's preference The discount factor β is set to be 0.99, which implies a 4% annual real rate. I choose the disutility of labor supply Ψ to generate a steady-state employment rate of 60%.

New Keynesian Block Following Ottonello and Winberry (2020), I set the elasticity of substitution over intermediate goods γ to be 10, implying a steady-state markup of 11%. I set the Rotemberg (1982) price adjustment cost $\varphi = 90$ to generate a Phillips curve slope equal to 0.1 and φ_π, the weight on inflation in the reaction function, to be 1.25, which is in the middle of the range commonly considered in the literature.

[Table 1.5 Here]

Simulated Method of Moments

The SMM proceeds as follows: a set of data moments Ψ^A is selected for the model to match. For an arbitrary value of θ, the dynamic program is solved and the policy functions are generated. These policy functions are used to compute a simulated data panel. The simulated moments $\Psi^S(\theta)$ are then calculated from the simulated data panel, along with an associated criterion function $\Gamma(\theta)$, where $\Gamma(\theta) = (\Psi^A - \Psi^S(\theta))' W (\Psi^A - \Psi^S(\theta))$, which is a weighted distance between the simulated moments $\Psi^S(\theta)$ and the data moments Ψ^A. The optimal parameter estimate $\hat{\theta}$ is obtained by searching over the parameter space using the annealing algorithm (see Appendix A.3 for more details). The value $\hat{\theta}$ minimizes the criterion function:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} (\Psi^A - \Psi^S(\theta))' W (\Psi^A - \Psi^S(\theta)). \tag{1.25}$$

Here, θ is a vector of five parameters: equity fixed and variable issuance costs λ_0 and λ_1, to match the average frequency of equity issuance and the ratio of new equity issuance to lagged total assets; unit loan issuance cost ξ_0 and unit bond issuance cost ξ_1, to match the average leverage and bond share; and fixed production cost c_f to match the annualized default rate and the credit spread of 10-year Baa corporate bonds.

Simulation

The empirical targets are based on the sample set I use for the empirical evidence above: quarterly Compustat data from 1990Q2 to 2018Q4. To compute the corresponding firm-level moments from the model, I simulate a panel of 10,000 firms for 200 quarters in total, including a 100-quarter burn-in period. The mass of firms is constant over time. I exclude defaulting firms when I calculate the moments.[28] I simulate 50 artificial samples and report the cross-sample average results as model moments in Table 1.6 and 1.7. The tables show the cross-simulation averages of the mean and standard deviation of the investment rate,

[28] I also exclude firms that are less than two years old when I calculate the sample autocorrelation of leverage.

profitability, and leverage, autocorrelation of leverage, frequency of new equity issuance, ratio of average equity issuance to total assets, credit spreads, and average bond ratio.

[Table 1.6 and 1.7 Here]

1.4.3 Value and policy functions

Figure 1.5 shows the optimal value and policies of firms with average productivity and debt under high rate and low rate economies.[29] It plots the value of equity (top left panel), investment rate (top right panel), (total) debt issuance rate (bottom left panel), and the price of the (defaultable) bond (bottom right panel). Each line in the figure corresponds to the economy with a specific interest rate. The solid blue line refers to the economy in a good state (low rate), and the dashed red line refers to the economy in a bad state (high rate).

The equity value is increasing in its capital stock while the investment rate declines. Conditional on capital, firms in a good state have a higher firm value and investment rate relative to firms in a bad state. The total debt issuance rate increases in the capital stock when the firm is small and lacks internal funds. Firms issue more debt when the interest rate is high. The total debt issuance decreases in the capital stock when a firm is large. Firms issue more debt in a good state because debt becomes more valuable as a result of lower default risk and, therefore, higher prices. Conditional on firms' idiosyncratic state, the overall cost of investment is lower, and investment opportunities become more profitable in a good state.

1.5 Quantitative Analysis

1.5.1 Cross-sectional Debt Composition

To begin, I provide steady-state cross-sectional evidence to validate the model. I show that the cross-sectional unconditional distribution of leverage, the distribution of loan share across firm size, and the life-cycle dynamics of firms implied from this model are in line with the key features of the data emphasized by

[29]Figure 1.5 shows the optimal value and policy functions of a partial equilibrium model in which the discount factor follows an AR(1) process, and therefore the interest rate is a state variable. The details of the partial equilibrium model can be found in Appendix A.2.

the firm dynamics literature.

Unconditional distribution. Panel A in Table 1.8 shows the unconditional distributions of leverage in the model and the data. I report the mean and the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles across firms. The model generates a reasonable cross-sectional leverage distribution with estimated percentiles close to those in the data, even though the model generates a relatively lower leverage ratio, 0.571 at the 95^{th} percentile, compared to 0.645 in the data.

Size. Size is a key dimension of firm heterogeneity. Figure **??** shows how the loan ratio covaries with firm size in the data and the model. Size is measured as lagged total assets. I sort loan shares by size quintiles. The data are shown in the red bars. The black bars show the corresponding values implied from the model. As in the data, the model is able to generate a hump-shaped distribution in the loan ratio.

Life-cycle dynamics. The initial value of capital that new entrants carry is calibrated to match the employment share of young firms (firms less than 1 year old) in the data. Panel B in Table 1.8 shows the untargeted employment share of firms in different age groups. In the data, the share of employment in firms less than 1 year old, between 1 and 10 years, and over 10 years are 0.02, 0.21, and 0.76, respectively.[30] Since the data sample covers 115 quarters in total, I only consider firms that are no older than 30 years in the simulated sample. The corresponding moments implied from the model are 0.015, 0.268, and 0.717.

Cross-sectional determinants of debt structure. The previous literature has established some stylized facts about the cross-sectional determinants of choice between loans and bonds. Houston and James (1996) and Johnson (1997) find that reliance on bank borrowing is decreasing in firm size and overall leverage. Denis and Mihov (2003) show that the primary determinant of firms' choice of debt instruments is their credit quality. Public borrowers are larger and more profitable, have a higher proportion of fixed assets to total assets, and have higher credit ratings relative to firms that borrow from either banks or non-bank private lenders. Table 1.9 examines the model-implied cross-sectional distribution of debt structure in the following regression test:

$$\text{Loan Share}_{i,t} = \alpha_i + \Gamma' X_{i,t} + \epsilon_{i,t}, \tag{1.26}$$

where Loan Share is defined as the ratio of loans over the total of loans and bonds. The expression $X_{i,t}$ is a

[30] Data are from Ottonello and Winberry (2020).

set of firm characteristics, including leverage, a dummy for credit rating, profitability, size, tangibility, and market-to-book value. The dummy for credit rating takes the value of one if the credit spread is zero and takes the value of zero if the credit spread is positive. The correlation between leverage and size, leverage, and tangibility are -0.23 and -0.89. Columns (1) to (5) report the univariate regression where the firm-level loan share is decreasing in firm leverage, credit rating, market-to-book value, and profitability but increasing in tangibility, consistent with the facts documented from the data.

1.5.2 Capital, Debt Structure Dynamics, and Interest Rate Risk

As documented in the empirical part of the paper, large firms switch towards loan financing, while small firms raise more equity after the tightening of monetary policy. The objective of this subsection is to show how the model can reproduce these empirical patterns with credit market frictions and risk prices of aggregate shocks.

I now quantitatively analyze the effect of monetary shock ϵ_t^m. The economy is initially at the steady state and unexpectedly receives a $\epsilon_0^m = 0.0025$ innovation to the Taylor rule, which reverts to 0 according to $\epsilon_{t+1}^m = \rho_m \epsilon_t^m$ with $\rho_m = 0.5$. I compute the perfect foresight transition path of the economy as it converges back to the steady state. To compare our model to the data, I simulate a panel of 10,000 firms in response to a monetary shock and estimate the baseline empirical specification using simulated data.[31] I assume that the high-frequency shocks ϵ_t^m that we measure in the data are innovations to the Taylor rule in the model. I estimate the regressions using data from 1 year before the shock to 12 years after the shock.

Model predictions are generally consistent with what we observe in the data. The panel regression results are shown in Table 1.10, which reports the average effect on the credit spread and the heterogeneous effects on the loan share and equity share. Column (3) of Table 1.10 shows that the spread between bonds and loans widens as the interest rate increases. This is because loan lenders have lower risk exposure due to seniority and collateral requirement. The expected loss of bond lenders increases more. It is costly to cut down investment, which generates countercyclical demands for external financing despite higher interest rates. As a result, large, less risky firms with ample unused collateral substitute loans for bonds. Firms with

[31] In the model, I use a time fixed effect rather than a sector-time fixed effect because the model does not contain multiple sectors. In addition, I do not include the subset of control variables $Z_{i,t-1}$, which are outside the model.

a median degree of default risk choose a higher loan share. Small, constrained firms have to raise more equity as they run out of collateral. The positive estimate of the loan share elasticity in column (1) and the negative estimate of the equity share elasticity in column (2) confirm the heterogeneous financing patterns.

1.5.3 Inspecting the Mechanism

This section performs the counterfactual analysis of key parameters that determine the loan-bond trade-off and substitution elasticity. I use simulated data as a laboratory to examine how the production fixed cost, debt, and equity issuance costs quantitatively affect the substitution between loans and bonds. Table 1.11 shows the key model moments from various model specifications. I compare the baseline model with (1) a model with an equal debt issuance cost for loans and bonds, (2) a model with the production fixed cost increased by 10%, and (3) a model with the variable equity issuance cost reduced by one-half.

In model (1) when intermediation costs are set the same for both loans and bonds, firms always prefer loans until they are constrained. This leads to a counterfactually very low bond share of 7% in the economy, compared to 76% in the data. The sensitivity of substitution (the coefficient of the interaction term between monetary shocks and firm size) declined by one-third, compared to the baseline model, due to less loan financing flexibility. In model (2), a 10% increase in the production fixed cost raises the default probability and bond spread by 60% and 37%, compared to the baseline model. The economy has lower leverage of 9%, compared to 21% in the data sample. The low leverage raises the substitution elasticity by one-half due to more financing flexibility. In model (3), a one-half reduction in equity issuance costs leads to a 10% drop in the leverage, a 3% drop in the bond share, as well as a 20% rise in equity financing. The elasticity of substitution becomes insignificant and close to zero since firms rely more on equity financing.

1.5.4 Model Implications

This section studies the model implications on credit flows and corporate investment. First, I document a heterogeneous effect of monetary shocks on firm investment. Second, I investigate the responses of key aggregate variables to monetary shocks.

Real Effect: Investment

In the model, the expanding demands for loan financing among large firms crowd out the bank credit to small, bank-dependent firms as a result of the finite debt supply. Therefore, constrained, bank-dependent firms have to disproportionately reduce investment after tight money. This suggests that debt composition is an important factor in determining investment elasticity: the firm with a higher loan share (less unused collateral) is more responsive. Here, I revisit this finding in the real and simulated data following the regression specification:

$$\Delta log k_{i,t+1} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times \text{Loan Share}_{i,t-1} + \delta\text{Loan Share}_{i,t-1} + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \quad (1.27)$$

The results are shown in Table 1.12. In column (1), -0.137 indicates that a 25 basis points interest rate hike reduces the average investment rate by 0.38%, compared to an average quarterly change in capital of 1.46%. The coefficient estimate of the interaction term is negatively significant at -0.130, which means that small, bank-dependent firms are more responsive to monetary shocks, as they are lack of unused collateral to hedge against interest rate risk. Column (2) shows consistent results using simulated data from the model.

Aggregate Implications

To understand the role of credit substitution in the transmission mechanism of monetary policy, Figure 1.7 plots the impulse responses of key aggregate variables to a 25 basis points interest rate hike. A positive shock to the nominal rate lowers the inflation rate as a result of sticky prices and therefore generates a larger increase in the real rate. The high rate depresses the investment demand by raising the cost of capital. It also depresses consumption demand from the household as a result of the standard intertemporal substitution. Overall, it reduces consumption by 0.37%, output by 1.4%, capital by 0.32%, and total debt by 1.55%. In addition, this model quantitatively reverses the traditional bank lending channel by generating a short-run expansion, 5% in five quarters, in bank loans, accompanied by a contraction, 1.9% in five quarters, in corporate bonds. A 25 basis points nominal rate hike leads to a 2.25% decline in the bond share.

1.6 Discussion

1.6.1 Revolver Lines of Credit versus Term Loans

I now inquire how revolvers or term loans change in response to interest rate risk. I follow Berg et al. (2016) in classifying loan facilities as term loans or revolver lines of credit.[32] The full sample consists of 71% revolving credit facilities and 29% term loans. Figure 1.8 plots the credit distribution across firm size for credit lines and term loans separately. Most of the loan credit is issued to large firms with total assets over 1 billion. On average, term loans have a longer maturity than credit lines, which is independent of borrowers' size. In Table 1.13, I perform the subsample analysis of credit lines or term loans. In panel A, firms switch to credit lines more than term loans, which is both statistically and economically more significant. In panel B, a significant increase in the average loan spread for credit lines suggests an increase in demand for credit lines, which is consistent with the results in panel A.

1.6.2 Supply-side effects

Financial frictions, market power, and bank regulation affect transmission of monetary policy. The bank reserve channel argues that a high federal funds rate raises the opportunity cost of holding reserves, thus contracting deposit creation. The bank capital channel shows that a high federal funds rate reduces bank capital because of a balance-sheet maturity mismatch and thus constrains banks' capacity to lend. The effects of bank market power are different in the deposit and loan markets. In a high rate environment, the deposit market power channel predicts that banks charge higher markups on deposits, thus leading to a further contraction in deposits and loans, while the loan market power channel predicts the opposite: banks reduce markups on loan rates to mitigate the effects of monetary tightening on loan demand (Scharfstein and Sunderam (2016)).

To control for the supply-side effect, I merge the final sample with lenders' balance sheet variables from FR Y9-C.[33] Bank characteristics, such as size, capital ratio, cost of funding, return to equity and ratio of

[32] I only include credit lines and term loans in the final sample. Term loans are defined as all loans with type "Term Loan," "Term Loan A"-,"Term Loan H," or "Delay Draw Term Loan," as indicated in the facility table in DealScan. Revolving loans are defined as all loans with type "Revolver/Line $<$ 1 Yr.," "Revolver/Line $\geq$ 1 Yr.," "364-Day Facility," "Limited Line," or "Revolver/Term Loan," as indicated in the facility table in DealScan.

[33] I only consider bank holding companies (BHCs) of U.S. banks that have issued over 50 loans in the sample

non-performing loan, and bank-time fixed effect, are included to control for the supply-side effect. Errors are clustered over bank k, firm i, and time t. The estimates of the following test are reported in Table 1.14:

$$\begin{aligned} y_{j,i,k,t} =& \alpha_{k,t} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\ &+ \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,t-1} + \Gamma_3' Y_{k,t-1} + \epsilon_{j,i,k,t}, \end{aligned} \tag{1.28}$$

where $Z_{i,t-1}$ is a set of firm controls, $W_{j,t-1}$ is a set of security controls, and $Y_{k,t-1}$ is a set of bank controls. The term $y_{j,i,k,t}$ is the total issuance amount from lender j to borrower i in quarter t, adjusted by banks' lagged total business loan in columns (1) to (3) or log(Loan Spread) in columns (4) to (6). It shows similar results: the increase in loan lending and loan spreads is more significant among large, high-rated firms with lower default risk.

1.6.3 Related to trade-off theory and MM theorem

The interest rate implications of the trade-off theory are often ignored in the literature. Graham and Leary (2011), Strebulaev and Whited (2012), Ai et al. (2020a), and Colla et al. (2020) provide good surveys of the capital structure and trade-off theory. This model discusses the trade-offs among a number of securities that can be used to finance endogenous investment. In the stationary equilibrium, beyond operating cash flows generated from production, the firm has the opportunity each period to take on new loans and bonds, as well as equity issuance. How does this model break the irrelevance theorem stated in Modigliani and Miller (1959)? The tax advantage of debt creates an incentive for leverage. As in the literature, bankruptcy incurs a liquidation cost, so full payment is not guaranteed for debt lenders. Firms face a borrowing limit on loans imposed by the collateral constraint. Finally, external financing incurs issuance costs for both debt and equity. All of these features create a deviation from the capital structure irrelevance.

1.7 Conclusion

In this paper, I argue that the countercyclical demand for loan financing among large firms is crucial in understanding the transmission of monetary policy. Using cross-sectional data, I document the new facts that

periods.

large, unconstrained firms substitute away from corporate bonds and toward bank loans as interest rate hikes widen the credit spread between bonds and loans. This crowds out bank lending to small, constrained firms. As a result, small firms have to issue more new equity while disproportionally reducing their investment. Moreover, this cross-sectional pattern has important aggregate implications, worsening the drop in capital investment and consumption following tight money, despite increasing the aggregate flow of business loans.

The findings in this paper generate important policy implications, as a strong demand-side effect overturns the supply-side channel, as emphasized in the traditional bank lending channel. This paper suggests that to mitigate credit misallocation after tight money, the optimal regulation policy is to provide easier bank credit access to small firms at a lower cost and, at the same time, prevent credit from being overdrawn among large firms. It sheds light on the intermediated debt market regulations that the central bank should implement when conducting monetary policy. Moreover, the discussions about firms' financing flexibility and the relevant policy interventions can be extended to other severe crises, such as the COVID-19 crisis, in future academic and policy research.

Table 1.1. Summary Statistics

Table 1 reports the summary statistics of key variables. Panel A presents the summary statistics of monetary policy shocks and aggregate corporate debt series from 1990Q2 to 2018Q4. Monetary policy shocks are estimated using an event study strategy. There are 76 daily contractionary shocks and 112 expansionary shocks in the sample. Aggregate nonfinancial corporate debt series are obtained from the Flow of Funds L.103. Panel B presents the summary statistics of loan origination data from DealScan and bond issuance data from FISD. Key variables of firm borrowers by their debt compositions are shown in panel C.

Variable	Mean	Median	Std Dev	Min	Max	N
Panel A: Aggregate Time Series of Monetary Policy Shocks and Corporate Debt						
Fed Funds Rate (High Freq; %)	-0.0155	0	0.0759	-0.467	0.163	255
Policy News Shocks (High Freq; %)	0.0004	0.0068	0.0403	-0.243	0.0986	200
Fed Funds Rate (Quarterly; %)	-0.0346	-0.0061	0.0906	-0.428	0.237	115
Policy News Shocks (Quarterly; %)	0.0002	0.0105	0.0503	-0.292	0.0873	95
Target Component (Quarterly; %)	-0.0003	0.0152	0.0574	- 0.239	0.101	59
Path Component (Quarterly; %)	0.00001	0.0007	0.006	-0.015	0.014	59
Loan/Total Debt	0.148	0.121	0.046	0.075	0.236	115
Bond/Total Debt	0.518	0.502	0.056	0.386	0.611	115
Loan Growth (%)	-0.078	0.381	3.583	-11.999	8.795	115
Bond Growth (%)	0.925	0.864	1.275	-1.803	4.328	115

To be continued

Variable	Mean	Median	Std Dev	25%	75%	N
Panel B: Corporate Debt						
Bank Loan from Dealscan (All Compustat firms)						
Loan Rate (bp)	489.12	469.00	231.20	290.78	668.75	24,686
“All-in-drawn” (bp)	191.37	175	127.16	100	250	25,479
Facility Amount (Million)	430.95	180	841.41	58.40	500	25,479
Maturity (Year)	4.16	5	1.80	3	5	24,866
Corporate Bond from FISD (All Compustat firms)						
Offering Yield (bp)	652.89	665.00	242.54	495.26	803.50	12,468
Spread (bp)	182.91	116.31	189.28	43.97	272.84	12,456
Offering Amount (Million)	414.04	300	454.67	100	500	12,468
Maturity (Year)	11.14	10.01	7.65	7.01	10.11	12,468
Bank Loan from Dealscan (Firms have access to both debt markets)						
Loan Rate (bp)	468.59	440.26	228.71	273.43	637.50	14,854
“All-in-drawn” (bp)	180.03	160	127.87	87.50	250	15,322
Facility Amount (Million)	584.60	290.23	1015.98	100	650	15,322
Maturity (Year)	4.25	5.00	1.85	3	5	14,977
Corporate Bond from FISD (Firms have access to both debt markets)						
Offering Yield (bp)	653.06	665.00	240.49	498.32	802	12,168
Spread (bp)	181.11	115.59	187.63	43.70	266.70	12,157
Offering Amount (Million)	411.50	300	452.56	100	500	12,168
Maturity (Year)	11.17	10.01	7.67	7.01	10.12	12,168

To be continued

Variable	Mean	Median	Std Dev	25%	75%	N
Panel C: Firm Variables						
Dependent Variables						
Prob(New Loan Issuance) (%)	4.91	0	0.22	0	0	418,728
ΔLoan Share (%)	5.79	0	5.94	-0.99	1.03	260,175
Prob(New Equity Issuance) (%)	6.63	0	24.88	0	0	418,728
ΔEquity Share (%)	1.08	0.70	10.18	-1.33	2.47	410,582
Control Variables						
Bank Debt =“No”, Public Debt =“No”; 4,358 Firms						
Size	3.84	3.76	1.50	2.75	4.83	146,223
Market-to-Book	2.24	1.44	2.26	0.88	2.68	136,452
Leverage	0.18	0.08	0.23	0.00	0.27	144,241
Investment Rate	0.05	0.02	0.13	-0.00	0.06	143,825
Sales Growth	0.02	0.02	0.40	-0.10	0.14	142,142
Liquidity	0.30	0.22	0.27	0.06	0.49	146,084
Tangibility	0.37	0.35	0.22	0.19	0.52	143,414
Dividend (dummy)	0.09	0.00	0.28	0.00	0.00	150,443
Bank Debt = “No”, Public Debt = “Yes”; 200 Firms						
Size	6.68	6.64	1.89	5.25	7.86	7,305
Market-to-Book	1.77	1.20	1.53	0.85	2.08	6,630
Leverage	0.35	0.31	0.28	0.15	0.51	7,196
Investment Rate	0.05	0.03	0.11	0.01	0.06	7,170
Sales Growth	0.02	0.02	0.24	-0.06	0.10	7,165
Liquidity	0.19	0.11	0.21	0.03	0.29	7,301
Tangibility	0.40	0.42	0.20	0.25	0.54	7,081
Dividend (dummy)	0.16	0.00	0.36	0.00	0.00	7,454
Bank Debt = “Yes”, Public Debt =“No”; 2,862 Firms						
Size	5.29	5.28	1.52	4.23	6.30	146,727
Market-to-Book	1.58	1.16	1.28	0.80	1.87	138,477
Leverage	0.21	0.17	0.21	0.04	0.33	144,505
Investment Rate	0.05	0.03	0.10	0.01	0.06	145,105
Sales Growth	0.02	0.02	0.23	-0.06	0.10	144,306
Liquidity	0.14	0.07	0.17	0.02	0.21	146,659
Tangibility	0.47	0.47	0.21	0.32	0.60	143,763
Dividend (dummy)	0.07	0.00	0.26	0.00	0.00	149,207
Bank Debt = “Yes”, Public Debt = “Yes”; 1,651 Firms						
Size	7.45	7.42	1.66	6.38	8.52	110,380
Market-to-Book	1.46	1.15	1.00	0.85	1.70	104,359
Leverage	0.32	0.29	0.22	0.17	0.43	108,859
Investment Rate	0.05	0.03	0.08	0.02	0.06	109,239
Sales Growth	0.02	0.02	0.18	-0.05	0.09	109,146
Liquidity	0.10	0.05	0.12	0.02	0.12	110,250
Tangibility	0.45	0.45	0.20	0.32	0.56	107,131
Dividend (dummy)	0.12	0.00	0.33	0.00	0.00	111,624

Table 1.2. Debt Financing Decision to Monetary Shocks

This table reports firms' differential debt financing decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\ &+ \delta (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

Columns (1) to (4) report debt financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm chooses bank loans over corporate bonds in quarter t. Columns (5) to (8) report debt financing decisions on the intensive margin, where the *dependent variable* is the change in flow of loans: Δlog(Loan) in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating, or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prob(Borrow from bank) (Extensive)				Δlog(Loan) (Intensive)			
ϵ_t^m	0.014***	0.014***	-0.007	0.018***	0.275***	0.236***	0.148*	0.259***
	(3.130)	(3.189)	(-0.965)	(3.953)	(3.332)	(2.804)	(1.672)	(3.058)
$\epsilon_t^m \times$ Size		0.007*				0.164**		
		(1.699)				(2.211)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.034***				0.426**	
			(3.681)				(2.036)	
$\epsilon_t^m \times$ D2D				0.018***				0.244***
				(3.726)				(2.936)
Observations	11850	11850	11850	11850	184939	184939	184939	184939
R^2	0.400	0.400	0.401	0.401	0.094	0.094	0.094	0.095
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.3. Equity Financing Decision to Monetary Shocks

This table reports firms' differential equity financing decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following regressions:

$$
\begin{aligned}
y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\
&+ \delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}.
\end{aligned}
$$

Columns (1) to (4) report equity financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm issues new equity in quarter t. Columns (5) to (8) report equity financing decisions on the intensive margin, where the *dependent variable* is the change of equity in quarter t over lagged total asset. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating, or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prob(Net new issuance) (Extensive)				ΔEquity share (Intensive)			
ϵ_t^m	0.215***	0.213***	0.203***	0.160***	0.124***	0.108***	0.111***	0.087***
	(4.469)	(4.393)	(3.785)	(3.014)	(6.322)	(5.386)	(4.976)	(4.420)
$\epsilon_t^m \times$ Size		-0.119**				-0.069***		
		(-2.307)				(-3.144)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.105				-0.045	
			(0.955)				(-1.371)	
$\epsilon_t^m \times$ D2D				0.001				-0.125***
				(0.031)				(-6.520)
Observations	298562	298562	298562	241825	241814	241814	241814	241814
R^2	0.141	0.141	0.141	0.149	0.133	0.134	0.133	0.134
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.4. The Effect of Monetary Shocks on Credit Spreads

This table reports the impact of monetary shocks on debt prices. Coefficients are estimated from the following regressions:

$$Credit\ Spread_{j,t} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1}))$$
$$+\delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,t-1} + \Gamma_3' Y_{t-1} + \epsilon_{j,t}.$$

Columns (1) to (4) report the results of loan spreads ("All-In-Drawn"), which is defined as the difference between the loan rate and the three-month LIBOR. Columns (5) to (8) (columns (9) to (12)) report the results of bond spreads, which is defined as the difference between the offering yield and three-month LIBOR (maturity-matched interest rate swaps). Column (13) report the results of the pooled sample of loans and bonds. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is the firm size, credit rating, or distance to default in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. $W_{j,t-1}$ is a set of debt characteristics including the logarithm of borrowing amount and maturity. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Separated Sample												Pooled Sample
	Loan Spread				Bond Spread (3M LIBOR)				Bond Spread (Swaps)				Credit Spread
ϵ_t^m	0.039***	0.044***	0.041***	0.048***	0.188***	0.197***	0.188**	0.199***	0.077***	0.086***	0.055	0.086***	0.035***
	(4.898)	(5.332)	(3.538)	(6.014)	(6.758)	(6.651)	(2.199)	(7.096)	(4.031)	(4.325)	(0.942)	(4.576)	(3.042)
$\epsilon_t^m \times$ Size		-0.003				-0.005				-0.006			
		(-0.374)				(-0.217)				(-0.376)			
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.008				-0.019				0.005		
			(0.562)				(-0.217)				(0.089)		
$\epsilon_t^m \times$ D2D				0.020*				0.029				0.012	
				(1.940)				(1.198)				(0.649)	
$\epsilon_t^m \times \mathbb{1}$(Bond)													0.096***
													(3.982)
Observations	17429	17429	17429	17429	9982	9982	9854	9982	10078	10078	9949	10078	27616
R^2	0.711	0.712	0.712	0.712	0.595	0.596	0.607	0.597	0.697	0.699	0.713	0.698	0.600
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.5. Predetermined (Calibrated) Parameters for Baseline Model (Quarterly)

This table summarizes the predetermined calibrated parameters used to solve and simulate the model. All values are quarterly.

Description	Parameter	Value	Target Moment/Source
Panel A: Household			
Discount factor	β	0.99	Annual interest rate (4%)
Labor disutility	Ψ	1.148	Steady state employment rate (60%)
Panel B: Firm Producer			
Technology			
Capital coefficient	α	0.21	Predetermined calibrated
Labor coefficient	ν	0.64	Total returns to scale of 85%
Depreciation	δ	0.025	10% annual depreciation rate (BEA)
Capital adjustment cost	ϕ (ϕ^{+}/ϕ^{-})	0.1/6	Predetermined calibrated
Productivity			
Productivity persistency	ρ_z	0.90	Predetermined calibrated
Productivity volatility	σ_z	0.12	Predetermined calibrated
Financing			
Corporate income tax	τ	0.3	Nikolov and Whited (2014)
Collateralized value	θ	0.5	Li et al. (2016)
Coupon payment	c	0.01	Standard
Liquidation recovery value	χ	0.38	Moody's Recovery Database
Panel C: New Entrants			
Initial capital	k_0	1	Predetermined calibrated
Initial debt	b_0	0	Standard
Initial productivity mean	m	-1.2	Predetermined calibrated
Panel D: New Keynesian Block			
Demand elasticity	γ	10	Steady state markup (11%); labor share (58%)
Taylor rule coefficient	φ_π	1.25	Ottonello and Winberry (2020)
Price adjustment cost	φ	90	Phillips Curve slope (0.1)
Persistence of monetary shock	ρ_m	0.5	Ottonello and Winberry (2020)

Table 1.6. Predetermined (Calibrated) Parameters and Model Fit

This table reports moments generated by the model. I simulate 50 economies for 100 quarters. Each sample consists of 10,000 firms. This table shows cross-simulation averages. The data are from quarterly CRSP-Compustat files covering periods from 1990Q2 to 2018Q4.

Description	Parameter	Value	Target Moments	Data	Model
Capital depreciation rate	δ	0.025	Mean of investment rate	0.045	0.028
Capital adjustment cost	ϕ (ϕ^{+}/ϕ^{-})	0.1/6	Stdev of investment rate	0.083	0.088
Capital coefficient	α	0.21	Mean of profitability	0.018	0.019
Productivity volatility	σ_z	0.12	Stdev of profitability	0.051	0.033
Productivity persistency	ρ_z	0.90	Autocorrelation of leverage	0.896	0.908

Table 1.7. Estimated Parameters θ and Moments

This table reports the parameter estimates by simulated method of moments and the matched moments from both the data and the model. I simulate 50 economies for 100 quarters. Each sample consists of 10,000 firms. This table shows cross-simulation averages. The data are from the quarterly CRSP-Compustat file covering periods from 1990Q2 to 2018Q4. Data for the bond share are measured using the aggregate corporate debt data of the nonfinancial corporate sector from Flow of Funds L.103. Data for bond spreads are from FISD.

Parameters	Value	Std Error
ξ_0	0.00711	(0.0005)
ξ_1	0.00662	(0.0002)
λ_0	0.3021	(0.0256)
λ_1	0.1000	(0.0281)
c_f	0.0971	(0.0005)

Moments	$\mathbb{E}$ (Leverage)	$\mathbb{E}\left(\frac{\text{Bond}}{\text{Total Debt}}\right)$	$\mathbb{E}\left(\frac{\text{Equity}}{\text{Asset}}\right)$	Prob(Equity)	Credit Spread	Prob(default)
Model	0.204	0.789	0.075	0.113	1.60%	3.08%
Data	0.222	0.760	0.094	0.067	1.78%	3.00%

Table 1.8. Cross-sectional Leverage Distribution and Firm Life-cycle Patterns

This table reports the cross-sectional and life-cycle patterns of firms in the data and the model. Panel A reports the unconditional distribution of leverage: the 5^{th}, 25^{th}, mean, 75^{th}, and 95^{th} percentiles. Panel B reports the employment share of firms: less than 1 year old, between 1 and 10 years, and over 10 years.

Panel A: Unconditional Leverage Distribution

	5^{th}	25^{th}	Mean	75^{th}	95^{th}
Data	0	0.029	0.223	0.348	0.645
Model	0	0.006	0.204	0.365	0.571

Panel B: Life-cycle Pattern (Employment share)

	N_1	N_{1-10}	N_{10}
Data	0.02	0.21	0.76
Model	0.015	0.268	0.717

Table 1.9. Cross-sectional determinants of debt structure (Simulation)

This table reports the cross-sectional determinants of the debt structure using the simulated data of 10,000 firms from the estimated model. The coefficient estimates are obtained from the following regression:

$$\text{Loan Share}_{i,t} = \alpha_i + \Gamma' X_{i,t} + \epsilon_{i,t},$$

where loan share is defined as the ratio of loans over the total amount of loans and bonds. $X_{i,t}$ is a set of firm characteristics including leverage, a dummy for credit rating, profitability, and tangibility. The dummy for credit rating takes the value of one if the credit spread is zero and takes the value of zero if the credit spread is positive. The firm fixed effect is indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
			Loan Share		
Leverage	-0.599***				
	(-86.76)				
Tangibility		0.691***			
		(89.14)			
Credit Rating			-0.278***		
			(-87.50)		
Profitability				-3.437***	
				(-122.32)	
Market-to-Book					-0.181***
					(-57.49)
Observations	986908	972901	986908	972901	986908
R^2	0.227	0.218	0.191	0.241	0.174
Firm FE	Y	Y	Y	Y	Y

Table 1.10. Dynamic Responses of Capital and Debt Structure to Interest Rate Risk

This table reports the dynamic responses of firms' financing decisions in response to interest rate shocks using the simulated data. Columns (1) and (2) show the heterogeneous responses in the loan and equity share, and column (3) shows the average effect on the credit spread. Firm and quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level. ΔLoan Share is winsorized at the 5% level, and other variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ΔLoan Share	(2) Δ(Equity Share)	(3) Relative Spread
ϵ_t^m			0.11
$\epsilon_t^m \times \text{Size}_{i,t-1}$	0.179	-0.066	
Observations	487,151	524,734	520,740
R^2	0.065	0.687	0.749
Firm & quarter FEs	Y	Y	Y

Table 1.11. Counterfactual Analysis

This table reports the key estimated parameters (panel A), the matched moments (panel B), and the elasticity of debt substitution (the coefficient of $\epsilon_t^m \times$Size in panel C) from four model specifications. "Baseline" is the benchmark model; model (1) sets equal intermediation costs for loans and bonds; model (2) raises the production fixed cost by 10%; and model (3) reduces the debt issuance costs by one-half.

	(1) Data	(2) Baseline	(3) Model (1)	(4) Model (2)	(5) Model (3)
A: SMM estimated parameters					
λ_0		0.3021	0.3066	0.1446	0.15
		(0.0256)	(0.0662)	(0.0151)	(0.0575)
λ_1		0.1	0.0477	0.0468	0.05
		(0.0281)	(0.6326)	(0.0006)	(0.0137)
ξ_0		0.0071	0.0070	0.0099	0.0064
		(0.0005)	(0.0085)	(0.0003)	(0.0094)
ξ_1		0.0066	0.0070	0.0094	0.0060
		(0.0002)	(0.0085)	(0.0004)	(0.0003)
c_f		0.0971	0.0990	0.1068	0.1013
		(0.0005)	(0.0441)	(0.0006)	(0.0071)
Criterion		0.0029	0.4757	0.0678	0.0051
Panel B: SMM estimated moments					
Avg. leverage	0.222	0.204	0.1874	0.0904	0.1837
Avg. bond ratio	0.76	0.789	0.0692	0.6765	0.7689
Avg. equity/asset	0.094	0.075	0.076	0.134	0.092
Prob(equity)	0.067	0.113	0.098	0.0703	0.0979
Bond spread	1.78%	1.60%	1.86%	2.25%	1.53%
Prob(default)	3%	3.08%	2.89%	5.12%	3.23%
Panel C: Elasticity of debt substitution					
$\epsilon_t^m \times$Size	0.077	0.122	0.088	0.187	-0.011

Table 1.12. Real Effects: Investment

This table reports the heterogeneous effects of monetary policy on firm investment using both real and simulated data from the model. Coefficients are estimated from the following regressions:

$$\Delta logk_{i,t+1} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times \text{Loan Share}_{i,t-1} + \delta\text{Loan Share}_{i,t-1} + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t+1},$$

where ϵ_t^m is the monetary shocks and $Z_{i,t-1}$ is a set of firm control variables including market-to-book ratio, liquidity, tangibility, leverage, a dummy for dividend payout, and a dummy for investment grade (long-term credit rating). Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and the inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4, excluding the financial crisis from 2008Q3 to 2009Q2. The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)
	$\Delta logk_{i,t+1}$	
	Data	Model
ϵ_t^m	-0.137*	-0.129*
$\epsilon_t^m \times$ Loan Share$_{i,t-1}$	-0.130*	-0.280***
Observations	222,336	520,740
R^2	0.131	0.749
Firm & Quarter FEs	Y	Y

Table 1.13. Loan Types: Credit Lines versus Term Loans

This table reports firms' differential debt choices and loan spread in response to monetary shocks in quarter t on the extensive margin, for credit lines and term loans separately. Coefficients are estimated from the following regressions:

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) \\ &+ \delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

In panel A, columns (1) to (4) report debt choices between credit lines and bonds. Columns (5) to (8) report debt choices between term loans and bonds. Panel B reports the effects on the credit spread. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating, or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, leverage, and a dummy for the dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and the inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Credit Lines				Term Loans			
	Panel A: Prob(Borrow from bank) (Extensive)							
ϵ_t^m	0.018***	0.019***	-0.009	0.022***	0.004	0.005	0.009	0.007*
	(3.933)	(4.001)	(-1.228)	(4.831)	(1.031)	(1.293)	(0.888)	(1.754)
$\epsilon_t^m \times$ Size		0.009**				0.006		
		(2.068)				(1.288)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.043***				-0.004	
			(4.645)				(-0.397)	
$\epsilon_t^m \times$ D2D				0.021***				0.006
				(4.267)				(1.340)
Observations	11399	11399	11399	11399	7788	7788	7788	7788
R^2	0.406	0.407	0.408	0.408	0.533	0.534	0.534	0.534
	Panel B: Loan Spread							
ϵ_t^m	0.019***	0.026***	0.030***	0.030***	0.035	0.054**	0.012	0.061**
	(2.806)	(3.645)	(2.905)	(4.126)	(1.530)	(2.268)	(0.494)	(2.535)
$\epsilon_t^m \times$ Size		-0.010				0.040*		
		(-1.587)				(1.727)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			-0.011				0.192***	
			(-0.874)				(3.173)	
$\epsilon_t^m \times$ D2D				0.021**				0.030
				(2.399)				(1.053)
Observations	11988	11988	11988	11988	4502	4502	4502	4502
R^2	0.741	0.741	0.741	0.741	0.640	0.641	0.642	0.641
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.14. Control for Supply-side Effects

This table reports firms' loan borrowing amount and cost in response to monetary shocks with the control of the supply-side effects. Coefficients are estimated from the following regressions:

$$y_{j,t} = \alpha_{k,t} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \delta(X_{i,t-1} - \mathbb{E}_i(X_{i,t-1})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,t-1} + \Gamma_3' Y_{k,t-1} + \epsilon_{j,t}.$$

Panel A reports the dollar issuance share, and panel B reports the loan spread of loan j from bank k to firm i in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating, or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of firm control variables including market-to-book ratio, liquidity, leverage, distance to default, and a dummy for the dividend payout. $W_{j,t-1}$ is a set of security control variables including maturity and a dummy for secured loans. $Y_{k,t-1}$ is a set of bank control variables including bank size, capital ratio, return to equity, and ratio of non-performing loans. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The bank-time fixed effect is indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the bank, firm, and time level, and t-statistics are in parentheses. All variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{\text{Issuance}_{j,t}}{\text{Total Business Loan}_{k,t-1}}$			log(Loan Spread)$_{j,t}$		
$\epsilon_t^m \times$ Size	0.364*			0.014		
	(1.897)			(1.653)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)		0.478*			0.043*	
		(1.752)			(1.912)	
$\epsilon_t^m \times$ D2D			0.259			0.033***
			(1.687)			(3.042)
Observations	13085	13085	13085	13078	13078	13078
R^2	0.569	0.568	0.568	0.705	0.705	0.706
Firm controls	Y	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y	Y
Debt controls	Y	Y	Y	Y	Y	Y
Bank-Time FE	Y	Y	Y	Y	Y	Y

Figure 1.1. Monetary Shocks

This figure plots the monetary shocks at the daily and quarterly frequency. The dashed red line represents the main measure of monetary shocks used in the baseline analysis: changes in fed funds futures prices around FOMC announcements. The solid blue line represents the policy news shocks from Nakamura and Steinsson (2018). The sample covers the periods from 1990Q2 to 2018Q4.

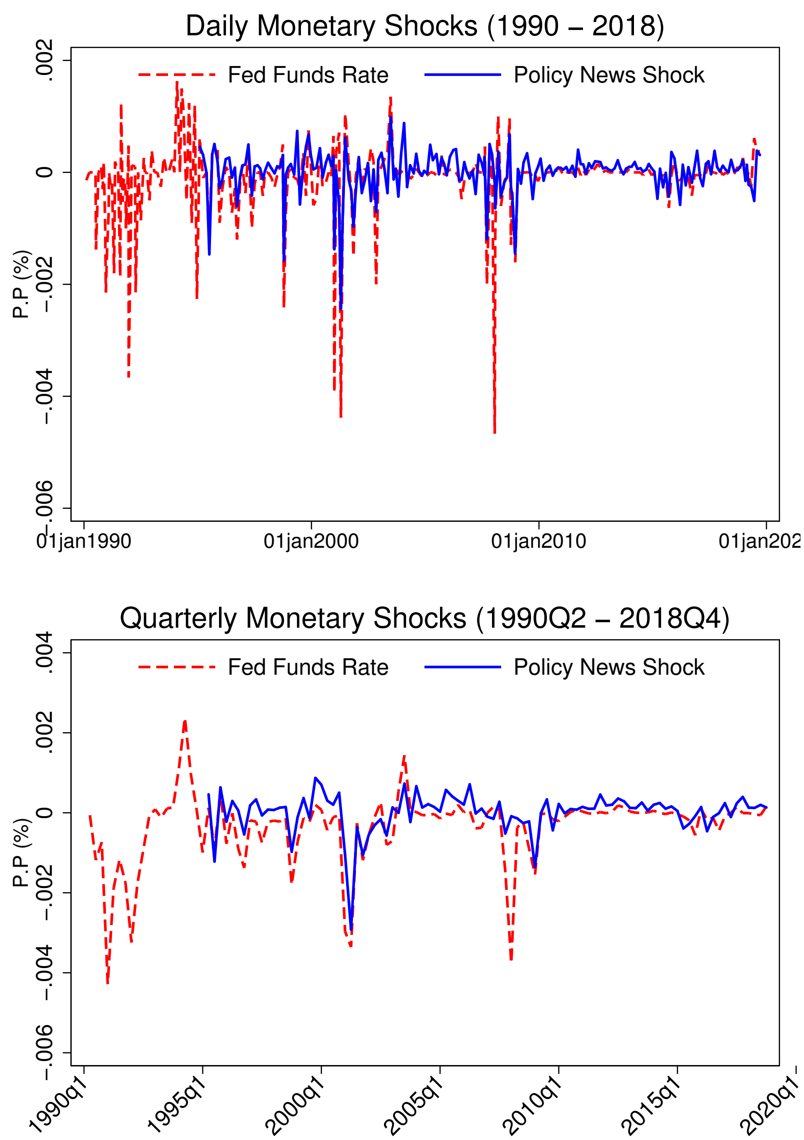
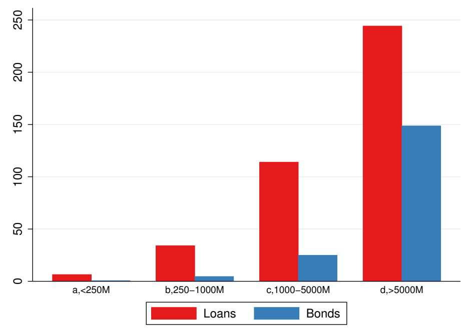


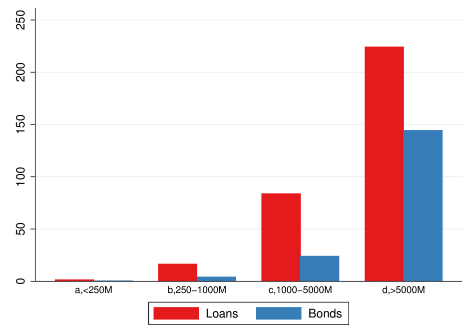
Figure 1.2. Debt Distribution across Firm Size: Loans and Bonds

The figures show the distributions of loan and bond new issuance across public firm size from 1990Q1 to 2018Q4. The top figures show the annual total dollar amount of debt issued to all public firms (left column) and firms with access to both markets (right column). The figures in the middle show the average debt maturities, and the bottom figures show the average credit spreads of debt issued to all public firms (left column) and firms with access to both markets (right column).

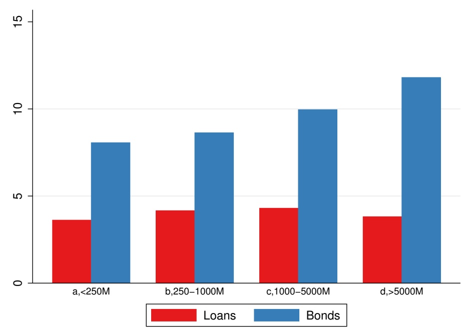
(a) Debt Amount to All Firms ($ Billion)



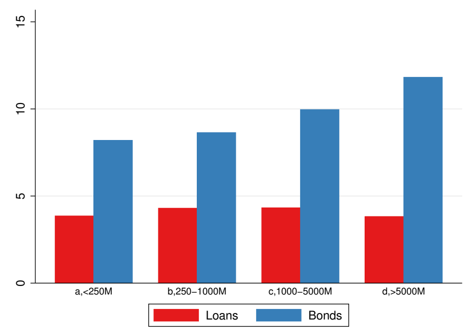
(b) Debt Amount to Firms with Access to Both Markets ($ Billion)



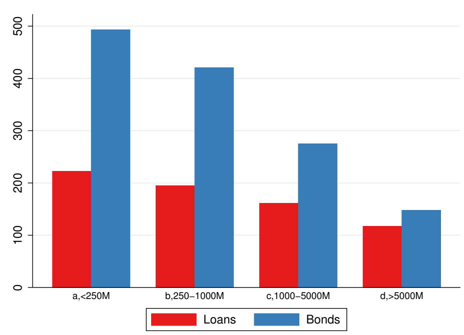
(c) Maturity to All Firms (Year)



(d) Maturity to Firms with Access to Both Markets (Year)



(e) Credit Spread to All Firms (bps)



(f) Credit Spread to Firms with Access to Both Markets (bps)

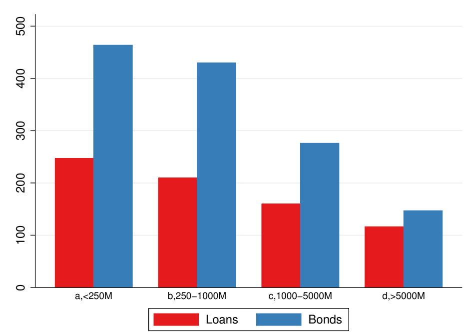


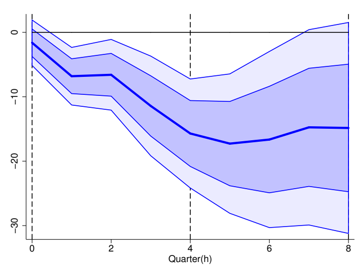
Figure 1.3. Dynamic Effects of Monetary Shocks on Aggregate Debt Composition

These figures plot the impulse response of aggregate corporate debt to a one standard deviation monetary shock ϵ_t^m based on the identification approach by Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016) at a quarterly frequency and the local projection specification. Coefficient estimates β_h from the following regressions are plotted over time horizon h:

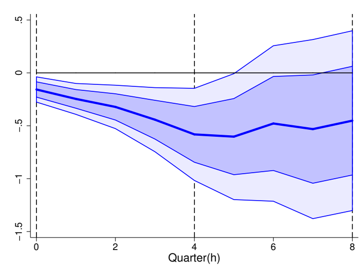
$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \epsilon_t^m + \Gamma_h Controls_{t-1} + \epsilon_{t+h},$$

where $h = 0, 1, 2, ..., 8$, and y is the (log) real credit (Billions of 1982 U.S. Dollars). The control variables include one year of lagged values of the monetary policy shock and one year of lagged values of the one-quarter change in the respective dependent variable, real GDP growth, inflation rate, unemployment, term spread, SLOOS tightening standards, and the forecasts of GDP growth and unemployment. The shaded areas are 68% and 90% error bands. Panels (a), (c) and (e) show the cumulative effects on bonds, loans, and total debt. Panels (b) and (d) show the cumulative effects on the growth rates. The debt series are obtained from the Flow of Funds L.103. The sample covers the periods from 1990Q2 to 2018Q4.

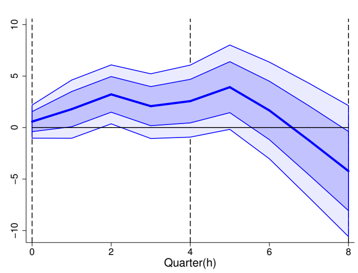
(a) β_h for ΔBond



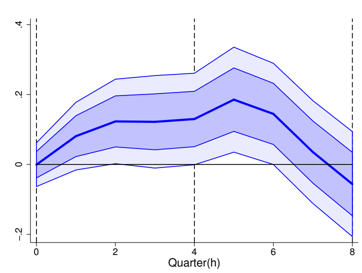
(b) β_h for Δlog(Bond) (%)



(c) β_h for ΔLoan



(d) β_h for Δlog(Loan) (%)



(e) β_h for Δ Total Debt

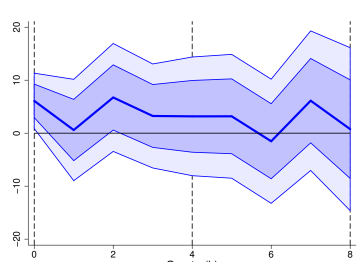


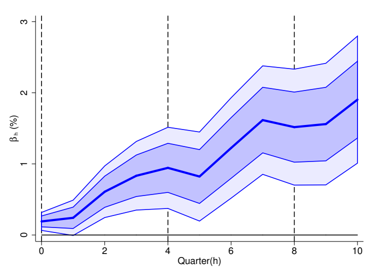
Figure 1.4. Dynamic Heterogeneous Effects of Monetary Shocks on Debt Composition

These figures plot the heterogeneous impulse responses of the firm-level loan flow and equity share to a one standard deviation monetary shock ϵ_t^m based on the identification approach by Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016) at a quarterly frequency and the local projection specification using data from Compustat. Coefficient estimates β_h from the following regressions are plotted over time horizon h:

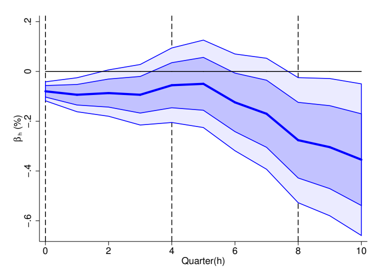
$$\Delta y_{t+h} = \alpha_i + \lambda_{s,t} + \beta_h \epsilon_t^m \times X_{i,t-1} + \delta_h X_{i,t-1} + \Gamma_h' Z_{i,t-1} + \epsilon_{t+h}$$

, where $h \in [0, 10]$. $X_{i,t-1}$ is firm size, credit rating, or distance to default (D2D). Additional control variables $Z_{i,t-1}$ include market-to-book ratio, liquidity, leverage, and a dummy for dividend payout. The shaded area are 68% and 90% error bands. Figures in the left (right) column show the cumulative effects of monetary shocks by firm size, credit rating, or distance to default on loan flow: $y = \Delta$ log(Loan) (equity share: $y = \Delta$Equity share). The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2).

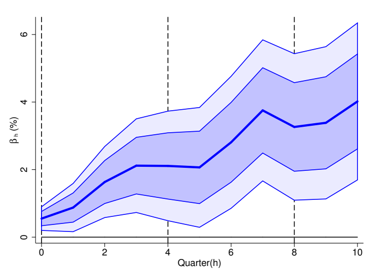
(a) β_h for Δ log(Loan) by Size (%)



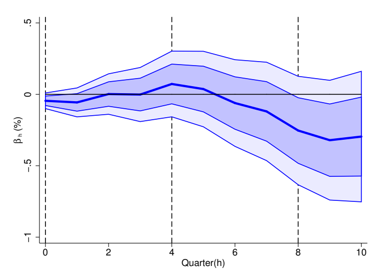
(b) β_h for ΔEquity Share by Size



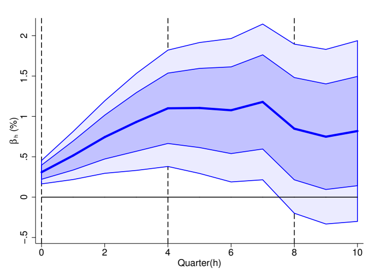
(c) β_h for Δ log(Loan) by Credit Rating (%)



(d) β_h for ΔEquity Share by Credit Rating



(e) β_h for Δ log(Loan) by D2D (%)



(f) β_h for ΔEquity Share by D2D

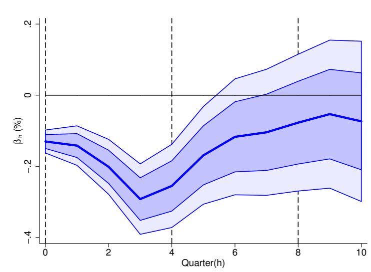


Figure 1.5. Optimal Value and Policy Functions

This figure plots the value of equity (top left panel), the policy for the investment-to-capital ratio (top right panel), the policy for the ratio of new (total) debt issuance to capital (bottom left panel), and the price of bond debt (bottom right panel) as functions of capital. The two lines correspond to firms with identical average idiosyncratic productivity and total debt levels, but in an economy with different interest rate levels. The solid blue line refers to an economy in a good state (low rate), and the dashed red line refers to an economy in a bad state (high rate).

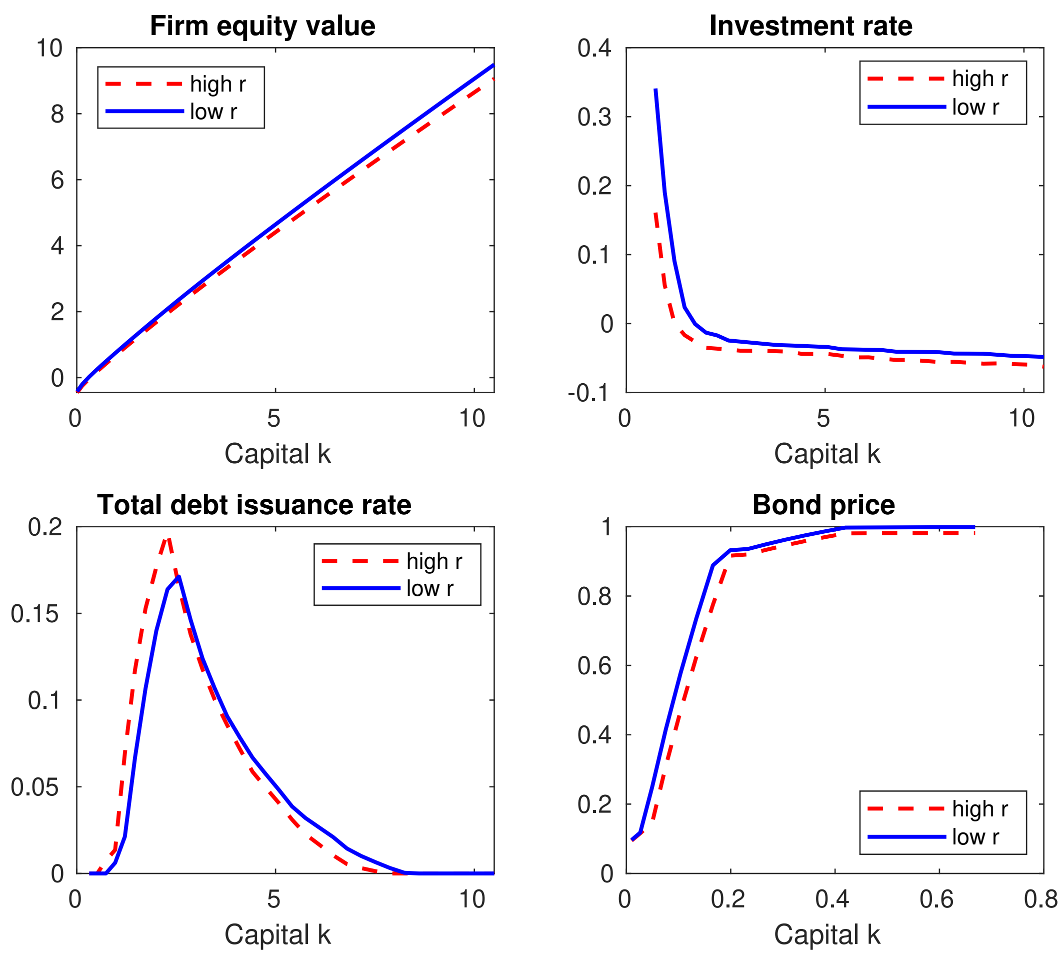


Figure 1.6. Firm Debt Conditional on Size

This figure shows the average loan ratio by size quintile. The data are shown by the red bars, and the black bars show the corresponding values implied from the model.

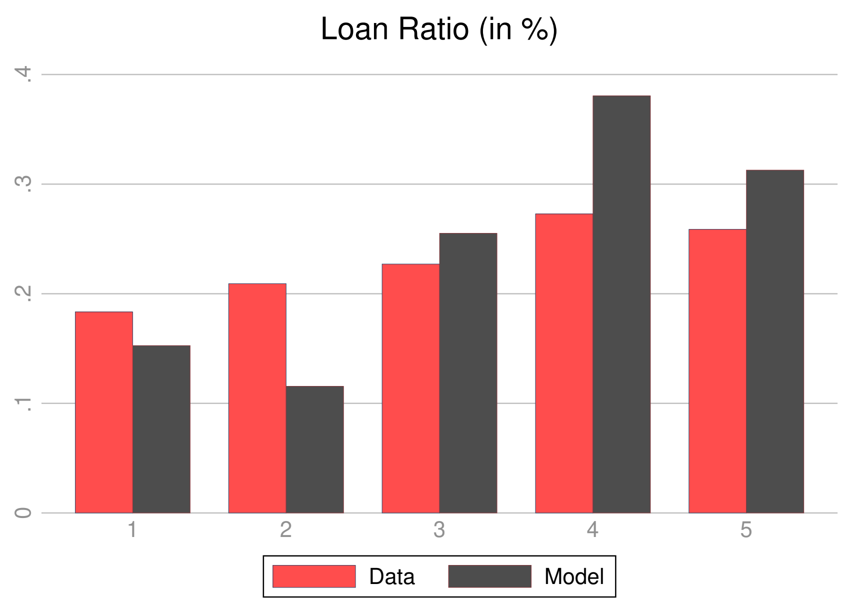
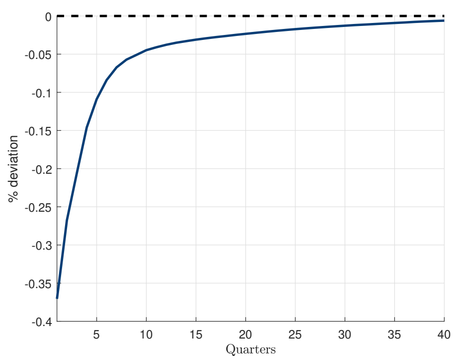


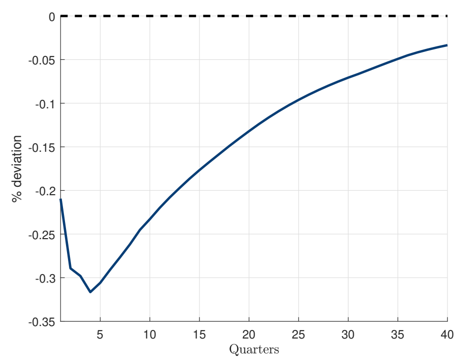
Figure 1.7. Aggregate Effects of Monetary Shocks

This figure plots the impulse responses of consumption, capital, total debt, bank loans, corporate bonds, and bond share to a 25 basis point innovation to the Taylor rule, which decays at rate $\rho_m = 0.5$ implied from the transition dynamics of the calibrated model.

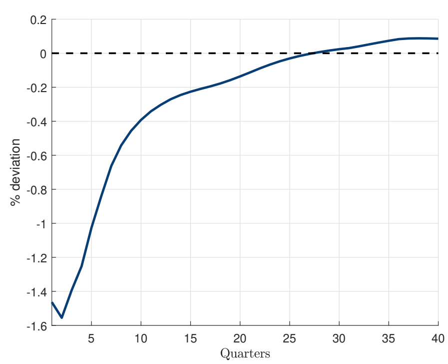
(a) IRF of Consumption



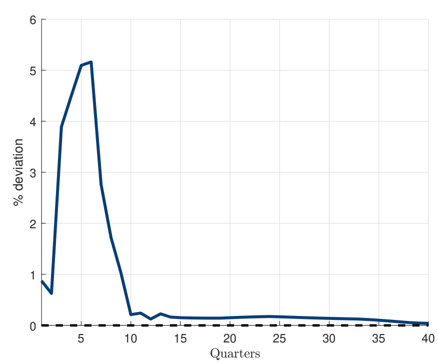
(b) IRF of Capital



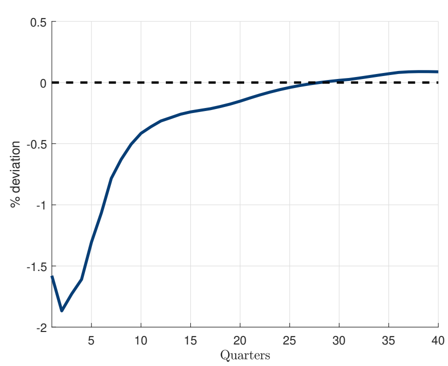
(c) IRF of Debt



(d) IRF of Bank Loans



(e) IRF of Corporate Bonds



(f) IRF of Bond Share

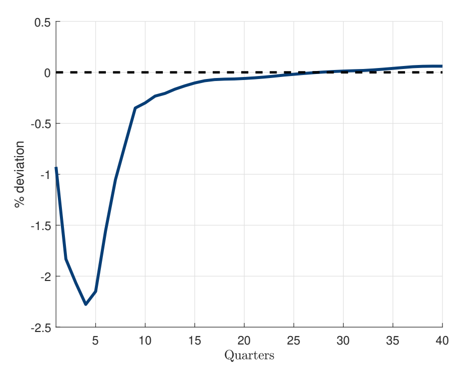
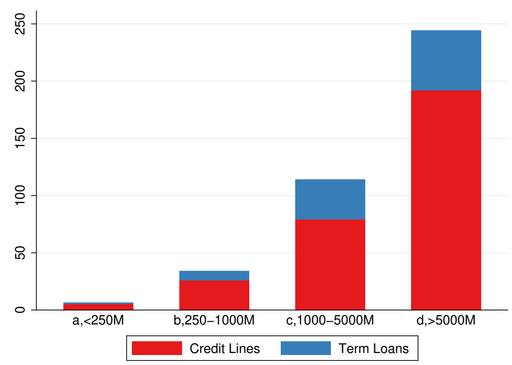


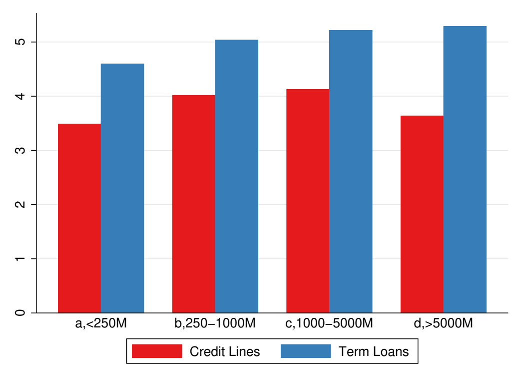
Figure 1.8. Loan Distribution across Firm Size: Credit Lines and Term Loans

The figures show the distributions of credit lines and term loans from DealScan across public firm size from 1990Q1 to 2018Q4. The top figure shows the total dollar amount of issuance, and the bottom figure shows the average maturity of credit lines and term loans issued to all public firms in different size groups.

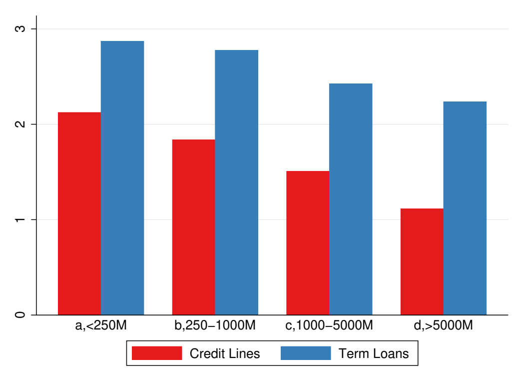
(a) Loan Amount to All Public Firms (in Billion)



(b) Loan Maturity to All Public Firms (Year)



(c) Loan Spread to All Public Firms (bps)



Chapter 2

Do Bankers Matter for Main Street? The Financial Intermediary Labor Channel

2.1 Introduction

This paper studies how the labor needs and labor costs of the financial sector affect aggregate risk and the real economy. Financial intermediaries (FIs) have been shown to play a central role in driving aggregate fluctuations over the business cycle. However, existing studies mostly focus on the financial leverage channel of FIs in affecting bank risk; the effect of FI labor needs and labor costs on FI health and the real economy is usually overlooked. We show that the labor channel of FIs is an important driver of asset prices and quantities, not only of the financial sector but also of the real economy.

Empirically, a high FI labor share (FLS) appears to be associated with stress in financial sector, which spills over into the real economy. A high FLS predicts high aggregate excess equity returns and borrowing costs; it predicts low growth of aggregate debt, investment, and output. Our estimates imply that when FLS is one standard deviation above its mean, the one year ahead excess equity return is 190bp higher, the one year ahead credit spread is 70bp higher, one year ahead debt, GDP, and investment are, respectively 3.5%, 0.5%, and 2% lower. In the cross-section, banks with a high labor share lend less and have higher credit risk. Firms connected to such banks borrow less, pay more to borrow, have higher credit risk, and lower earnings growth; they also invest less, especially if they are financially constrained.

To explain these empirical facts, we build a DSGE model where FIs face shocks to the quantity of labor needed to intermediate capital, we refer to these as FI labor need (FLN) shocks. FLN shocks are analogous to the "financial shocks" in Jermann and Quadrini (2012b) and Khan and Thomas (2013), but specific to the labor FIs need, as opposed to the collateral constraint shocks that they model. These shocks to the intermediation technology can be thought of as a reduced form way to model intermediary behavior in a changing investment environment.

We do not take a stand on the source of the FIs labor shocks, but we provide several possible channels: (*i*) if the investment environment deteriorates, for example due to worsening moral hazard or asymmetric information, then in order to avoid worsening returns on investment, FIs will require more labor to screen and to monitor their investments; (*ii*) default and litigation risk may be higher during recessions, leading to higher demand for debt collection and legal services by FIs;[1] (*iii*) if households lose trust in the financial system or have alternative investment opportunities or have too many choices due to more intense competition, then, in order to avoid losses in their funding, FIs will require more labor to market themselves to depositors and to manage client relationships; (*iv*) regulatory shocks, like Dodd-Frank or Sarbanes-Oxley, can require FIs to hire more people to deal with additional regulation;[2,3] (*v*) during the Covid-19 pandemic,

[1]For example the debt collection industry boomed in the aftermath of the 2007 financial crisis (Blumberg (2010) and Bassett (2008)), as did debt related lawsuits (Martin (2010)). This implies that the labor needs of debt holders increased.

[2]For example, the Wall Street Journal writes: "A labor-market squeeze and evolving regulatory pressures are driving demand for compliance officers ... sectors such as financial services beefed up their compliance departments following the financial crisis of 2008 and the enactment of new regulatory regimes like the 2010 Dodd-Frank Act... Cryptocurrency is one area that has heated up for compliance jobs" (Sun (2022)). Similarly, the New York Times writes "New regulation has long been one of Washington's unofficial job creation tools. After the enactment of the Foreign Corrupt Practices Act in the late 1970s, hundreds of lawyers and accountants were hired by companies to strengthen their internal controls. The Sarbanes-Oxley Act of 2002 became a boon for the Big Four accounting firms as public corporations were forced to tighten compliance in the wake of the Enron and WorldCom scandals. Now, the Dodd-Frank Act is quickly becoming such a gold mine that even Wall Street bankers, never ones to undercharge, are complaining that the costs are running amok" (Dash (2011)).

[3]A survey of banks by S&P Global (S&P Global Market Intelligence (2017)) provides additional evidence for the importance of FLN shocks in the context of Dodd-Frank. 49% of responders said compliance costs were up at least 20%, 59% said compliance costs now account for at least 10% of their annual expenses. "Operating in the current regulatory environment significantly drives up our overhead costs," said a Texas community banker; ""We just pass the lost revenue or cost onto the end consumer," said a community banker from Iowa; "It isn't profitable to make loans under $1 million" said a Florida community banker; "in 20 years I doubt we will be left with anything else besides megabanks... This will have a dramatic, chilling effect on small business creation and economic growth" said a credit union respondent.

banks were extremely busy with PPP loans, as they needed to verify various information about borrowers in a short period of time. An FLN shock may be direct, such as (iv), or could be an endogenous response to another shock, such as (i). In the latter case, we may think of FLS as a reduced form way to proxy for shocks to the labor component of the bank's production function. In the literature review section below, we discuss empirical evidence in support of some of these channels. In section 2.2.4 we show direct evidence that individual banks' increased regulatory compliance burden is associated with an increase in labor share, and in turn, less future lending and higher rates; we also show that aggregate regulatory shocks, as in (iv) affect the compliance burden and labor share.

In the model, a positive shock to FI labor needs per dollar of intermediated capital immediately increases FI costs and their labor share, which measures the payments to labor per dollar of value added. In principle, labor share need not rise if wages were to fall sufficiently, but since FI wages are tied to aggregate wages through labor market clearing, wages do not fall much.[4]

A positive shock to FI labor needs per dollar of intermediated capital is associated, both contemporaneously and in the future, with a fall in lending and a rise in lending costs. This happens because as it becomes more expensive for FIs to do business, they contract their balance sheets. In order to cover their higher labor costs, FIs must charge higher interest.

A positive shock to FI labor needs per dollar of intermediated capital is also associated with a contemporaneous fall in the equity return as it becomes more expensive for firms to raise capital, and as a result to produce. However, expected future equity returns are higher. This is because the economy has a limited capacity to provide equity financing to firms – modeled by a convex equity issuance cost – and as firms switch away from debt toward equity capital, investors demand higher return as compensation for the higher costs.

Finally, a positive shock to FI labor needs per dollar of intermediated capital is associated with lower investment and output, both contemporaneously and in the future. The fall in output happens because the drop in lending pushes firms away from their optimal capital structure, making them less productive and

[4] As shown in footnote 39, the aggregate wage is derived from labor demand in the productive sector $W_t = (1-\alpha)Z_t\left(\frac{K_t}{N_t}\right)^{\alpha}$. In this equation, the only variable that depends on FI labor demand is $N_t = 1 - N_{t,b}$. Since FIs hire approximately only 5% of the labor force, even large moves in FI labor $N_{t,b}$ have a relatively small (in percentage terms) effect on productive sector labor N_t, and therefore a relatively small effect on the aggregate wage.

because the hoarding of labor by financial intermediaries puts upward pressure on wages, making it more expensive for firms to produce. Because households are unwilling to significantly reduce consumption, lower output leads to a fall in investment, which further reduces future output as the capital stock is lower.

We verify the importance of FLN shocks by showing that a model with TFP shocks alone is unable to match the data along various dimensions. We also extend the model to allow for credit risk, wage rigidity, and labor adjustment costs; none of these extensions is able to substitute for FLN shocks. Importantly, we are able to identify the FLN shock by matching the dynamics of FI labor as a fraction of aggregate employment. In the data, the FI labor fraction rises when GDP falls, however, models without an FLN shock imply a falling share in bad times. Furthermore, because FLN shocks are the key driver of FLS in the model, we also provide an empirical identification by estimating an aggregate shock to FLS while controlling for various aggregate quantities and prices. The extracted shock captures the bulk of the variation in FLS and has similar predictive power for the aggregate variables of interest.

Although our model is about aggregate quantities, the same intuition holds for individual FIs. If a bank suddenly requires more labor to intermediate capital, the bank's labor share will rise and its lending will fall. Furthermore, if firms face switching costs when choosing their lenders, firms connected to the affected bank will be adversely affected. As discussed above, we empirically test these relationships at the aggregate, bank, and firm level. We find strong empirical support for the model: FI labor share appears to proxy for stress to lenders, which adversely affects the real sector and increases expected equity returns.

Literature review This paper builds on four broad literatures. First, the FI asset pricing literature, which studies how constraints on FIs affect asset prices and risk premia. Studies including Danıelsson et al. (2004), Gromb and Vayanos (2010), He and Krishnamurthy (2011), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Gromb and Vayanos (2018) have argued theoretically that FI financial leverage should matter for risk and asset prices because they are marginal investors when they are constrained. Empirical support for these theories has been found by, among others, He et al. (2017), Etula (2013), Adrian et al. (2014), and Haddad and Muir (2018); for example FI financial leverage is a priced factor for the cross-section of asset returns. Our paper contributes to this literature by showing that FI labor needs are an independent channel because FI labor share predicts stock market returns, cost of debt, banks' risk, and real outcomes, even when controlling for FI financial leverage.

Second, the macroeconomic literature studying the role of FIs in amplifying the shocks to business cycles.[5] Christiano et al. (2014) imbed agency problems associated with financial intermediation as in Bernanke et al. (1999) into a monetary dynamic general equilibrium model; they find volatility shocks are important in driving the business cycle. Gertler and Kiyotaki (2015) study the macro implications of banking instability in a DSGE model with financial accelerator effects and bank runs. Begenau and Landvoigt (2018) study the macroeconomic impact of capital regulation in a model with both commercial banking and shadow banking sectors. Elenev et al. (2018) investigate the macro-prudential policy in a large scale quantitative model with financially constrained producers and intermediaries. Diamond et al. (2020), Bolton et al. (2022), and Li (2022) all build macro models of intermediaries with a focus on the liquidity of either assets or liabilities. We complement this literature by showing that the labor needs and labor costs of the financial sector matter for FI health, which directly affects the loan supply to the real sector; this in turn affects the real investment and asset prices.

Third, the empirical literature investigating the relationship between FIs and firms' real decisions.[6] Peek and Rosengren (1997) document that shocks to Japanese stock market causes the US branches of Japanese banks reduce their loans, with the effect being stronger for weaker banks. Ivashina and Scharfstein (2010) document large drops in lending of banks during the financial crisis. Chodorow-Reich (2014) shows substantial effects of credit disruption in the 2008-2009 financial crisis on employment at the firm level, for firms connected to affected banks. We show that banks with higher labor share cut lending more and hence affect the real investment of their borrowers.

Fourth, this paper relates to the macroeconomic literature on wages and labor,[7] although only more recently has this literature begun to relate to financial economics.[8] On the other hand, financial economists have also recently begun exploring links between labor and asset prices both in structural models,[9] and

[5] Classic papers on the amplification of the frictions of financial intermediaries to aggregate shocks include Bernanke and Gertler (1989), Carlstrom and Fuerst (1997b), Bernanke et al. (1999), Jermann and Quadrini (2012b), Khan and Thomas (2013), etc.

[6] A partial list of papers include Bernanke (1983), Slovin et al. (1993), Gan (2007), etc.

[7] Examples include Pissarides (1979), Calvo (1983), Taylor et al. (1983), Taylor (1999), Shimer (2005), Hall (2005), Gertler and Trigari (2009).

[8] See Hall (2016) who reviews the recent literature and shows that a higher discount rate is associated with higher unemployment.

[9] Examples include Danthine and Donaldson (2002), Berk et al. (2010), Berk and Walden (2013), Petrosky-Nadeau et al. (2018), Belo et al. (2014), Donangelo (2014a), Li and Palomino (2014), Palacios (2015), Favilukis and Lin (2015), Zhang et al. (2014), Blanco and Navarro (2016), Donangelo et al. (2010), and Favilukis et al. (2020).

empirical analysis.[10] However, there has been relatively little work focusing on the labor of FIs specifically. One notable exception is Philippon and Reshef (2012), which studies the long term evolution of compensation in the financial sector.

Finally, there is a growing literature that provides empirical support for the importance of FI labor and shocks to FI labor productivity. Flanagan (2022) estimates that banks create 190bp of value added on their syndicated loans, most of which is paid to the bank's employees. He attributes most of this to the bank's screening and monitoring activities and shows that this value added was higher in more complex situations – consistent with our assumption that there are certain times or circumstances when banks require more labor to intermediate capital.[11] Sharpe and Sherlund (2016), Choi et al. (2022), and Ma (2022) all document the importance of labor capacity constraints for mortgage lenders; this implies that the amount of lending is tied to the number of loan officers, as in our model. These papers also document that when demand is high and lenders are at their capacity constraint, they switch toward borrowers who are easier to process, for example refinancing (as opposed to new originations) and high credit score borrowers - in effect, this makes loan officers more productive in good times. In addition, Fuster et al. (2022b) document that the price of intermediation fluctuates significantly, reflecting capacity constraints, and that in 2008-2014, the price of intermediation increased by about 30bp per year, reflecting higher mortgage servicing costs and an increased legal and regulatory burden. Finally, Fuster et al. (2022a) show that during the Covid-19 pandemic, there was a large and sustained increase in intermediation markups, due to pandemic related labor market frictions and operational bottlenecks.[12]

[10]Many papers have linked asset returns or financing decisions to various measures of operating leverage, most related to labor. These include Ruback and Zimmerman (1984), Abowd (1989), Hirsch (1991), Chen et al. (2011), Lee and Mas (2012), Simintzi et al. (2014),Weber (2015), Favilukis and Lin (2016), Gorodnichenko and Weber (2016), Tuzel and Zhang (2017), D'Acunto et al. (2018), Donangelo et al. (2019a), Donangelo (2018), Campello et al. (2017), and Qiu and Shen (2017).

[11]Specifically, he shows that the value added is higher for firms that are smaller, younger, and without a credit rating. It was also higher for firms previously audited by Arthur Anderson after its exit from auding following the Enron and Worldcom scandals.

[12]There is also a related literature on the busyness of agents impacting their financial decisions. (Fich and Shivdasani, 2006) show that when board members are busy, corporate governance is weaker. Kempf et al. (2016) show that firms whose shareholders are distracted are more likely to make bad decisions. Wang (2022) show that proxy advisors make worse recommendations when the proxy statement is more complex and when the advisors are especially busy.

2.2 Empirical evidence

In this section we explore empirical relationships between labor share in the financial sector and the fluctuations in asset prices, credit, and quantities of the real sector. We do so first, using aggregate, time series analysis of U.S. data, and second, using a cross-sectional analysis of bank-firm-level data.

In the aggregate-level time series analysis, we document that a high financial intermediary labor share (FLS) is associated with stress in equity markets, credit markets, and the real economy. Specifically, using aggregate data, FLS is negatively associated with contemporaneous stock market returns, but positively predicts future stock market returns and the Baa - Fed Funds spread; it is negatively associated with both contemporaneous and future debt growth, investment growth, and output growth. These empirical findings mirror the prediction of our model in section 3.2.

Using bank-level data, a bank holding company's labor share positively predicts the bank's risk, measured as expected default frequency (EDF); it negatively predicts its loan growth. Furthermore, in the bank-firm pair analysis, using Dealscan loan origination data, we show that firms connected to a bank with a high labor share experience lower debt growth, have higher expected default risk, pay more to borrow, and see lower earnings growth. Their investment growth is negative but not statistically significant, however it is significant for a subset of firms who are financially constrained. These empirical findings mirror the aggregate empirical findings. While our model only speaks to aggregate quantities, the mechanism in our model should also work at the individual bank level, and would be consistent with these empirical findings.

2.2.1 Aggregate-level time series analysis

This section performs time series analysis using aggregate data. We show that when the labor share of the financial sector is high, current excess equity returns are low, but future excess equity returns and the cost of corporate borrowing tend to be high. At the same time, current and future corporate debt growth, GDP growth, and investment growth tend to be low. We first describe the data, then the empirical specifications and the results.

Data and variable definitions

Our dependent variables of interest are non-financial sector debt growth, Baa minus Fed Funds spread, aggregate GDP growth, aggregate private investment growth, and market excess return. Our key independent variable is labor share in the financial sector (FLS), which is the ratio of compensation of employees to net value added of the financial business sector from Integrated Macroeconomic Accounts (IMA). As controls, we include aggregate labor share (LS), aggregate GDP growth, aggregate wage growth (ΔW), credit spread (CS), term spread (TS), price-dividend ratio (PD), and financial sector value added growth (ΔFVA). We additionally control for FI leverage ratios constructed from Adrian et al. (2014) (hereafter "AEM") and He et al. (2017) (hereafter "HKM"). The final sample for aggregate time series regressions contains annual data from 1961 to 2019.[13] Appendix section B.1 contains more detailed definitions of these variables as well as the summary statistics.

Descriptive statistics

Table 2.1 presents summary statistics for financial sector labor share (FLS), value added growth, and financial leverage ratios constructed from the literature ("HKM" and "AEM"). Other aggregate variables include GDP growth, non-financial corporate debt growth, investment growth, wage growth, consumption growth, and aggregate labor share. All the growth rates are calculated based on real quantities. The average FLS is 0.64, somewhat higher than the labor share for the aggregate economy, which is 0.55. The correlation of the two is just −0.02, suggesting that FLS contains different information than the aggregate labor share.[14] FLS is counter-cyclical, its correlation with real GDP growth is −0.30. FLS positively correlates with the financial sector leverage ratios but these correlations are 0.16 and 0.43, implying that FLS captures different information from financial leverage.

[13]We start in 1961 because that is the start of Integrated Macroeconomic Accounts (IMA) data and end in 2019 just before the Covid-19 pandemic. The time series of HKM (1970-2019) and AEM (1970-2012) are available for a shorter sample.

[14]Notably FLS does not display a downward trend in our sample, in contrast to the aggregate labor which has trended downward during the last 40 years. This implies that our econometric tests do not suffer the spurious tests issues due to non-stationarity raised in Granger and Newbold (1974).

FLS and excess equity return

In this subsection, we explore the relationship between FLS and excess aggregate stock market returns. Table 2.2 shows that FLS positively predicts excess market returns at 1-year, 3-year, and 5-year horizons (Panels B, C, D). The first column presents the results from a univariate regression; FLS positively and statistically significantly predicts returns with t-statistics of 1.96, 2.94, and 3.25 for 1-year, 3-year, and 5-year horizons respectively.[15] A one standard deviation increase in financial labor labor share corresponds to an increase by a factor of 1.27 in the 1-year ahead market excess return.[16]

The remaining columns present the results from bivariate regressions, with one control at a time. When adding controls, the coefficient on FLS is always positive. It becomes insignificant for 1-year ahead returns with some controls; it is positive and statisitcally significant in all 3-year and 5-year ahead specifications. Importantly, FLS remains significant when including either "HKM" or "AEM", the two variables frequently used to proxy for FI health.

Panel A shows that unlike future expected return, where the relationship is positive, the contemporaneous relationship between FLS and realized return is negative, though not statistically significant.

These results are in line with our model, where a positive shock to the financial intermediary sector's labor needs (FLN) causes an increase in FLS. The same shock is also associated with lower aggregate equity returns contemporaneously, but higher expected future equity returns. Contemporaneous returns are low because it will now become more expensive for firms to raise capital. Expected future returns are high because when FLS is high, firms shift toward more equity financing, which raises equity issuance costs, and leads investors to require higher compensation for holding equity.

FLS and credit markets

Next we turn to the impact of FLS on credit markets, specifically corporate debt growth and the cost of credit, measured by the spread between Baa bonds yields and the Federal Funds rate. We carry out exactly the same exercise as with market excess return in the previous subsection, but with these two dependent

[15] In our baseline regression, we use Newey-West standard errors with 13 lags. We also try 2, 4, and 8 lags. For some of these, the 1-year forecast becomes insignificant, although the 3-year and 5-year remain significant.

[16] Since the average historical equity premium is around 7%, this implies that the equity premium is 190 basis points higher.

variables; these results are presented in Table 2.3 for debt growth and Table 2.4 for the Baa - Fed Funds spread.

FLS negatively and significantly predicts aggregate credit growth, with t-statistics of -5.22, -5.88, and -3.87 for 1-year, 3-year, and 5-year horizons respectively (Panels B, C, D). The univariate R^2's are 0.24, 0.23, and 0.19. The strong statistical significance remains when we add controls. In Appendix Table B.2 we show that this is also true for financial sector credit growth.

FLS positively and significantly predicts the cost of credit, with t-statistics of 4.21, 2.42, and 1.78 for 1-year, 3-year, and 5-year horizons respectively (Panels B, C, D). The univariate R^2's are 0.14, 0.05, and 0.01. The strong statistical significance remains for the 1-year horizon when we add controls; for 3-year and 5-year horizons, all coefficients remain positive but some become insignificant with controls.

Panel A shows that the same relationships – negative between FLS and credit growth and positive between FLS and cost of debt – hold contemporaneously. One exception is that the Baa - Fed Funds spread contemporaneous slope on FLS becomes negative and insignificant when controlling for term spread. This is because the two spreads are very strongly contemporaneously correlated.

These results are in line with our model, where a positive FLN shock is associated with lower lending and higher cost of lending, both contemporaneously and in the future. As it becomes more expensive for financial intermediaries to do business, they contract their business activities, and therefore lend less. In order to cover their higher labor costs, financial intermediaries must charge higher interest. Firms are willing to pay higher interest because as lending is cut, they are further away from their optimal capital structure, thus the benefit of an extra dollar of debt, relative to equity capital increases.

FLS and real outcomes

Finally, we study the impact of FLS on real quantities, specifically aggregate GDP growth and investment growth. Again, the exercise is analogous to the ones in the previous two subsections, but with two new dependent variables; these results are presented in Table 2.5 for GDP growth and Table 2.6 for investment growth.

FLS negatively and significantly predicts GDP growth, with t-statistics of -2.23, -1.78, and -1.52 for 1-year, 3-year, and 5-year horizons respectively (Panels B, C, D). Similarly, FLS negatively and significantly predicts investment growth, with t-statistics of -2.64, -1.89, and -0.17 for 1-year, 3-year, and 5-year horizons respectively (Panels B, C, D). However, this predictability has a shorter horizon than for credit variables in the previous section as these results become statistically insignificant for some controls and for the 5-year horizon.

Panel A shows that that the same negative relationships between FLS and either GDP growth or investment growth hold contemporaneously, though it becomes statistically insignificant with some controls.[17]

These results are in line with our model, where a positive FLN shock is associated with lower investment and output, both contemporaneously and in the future. As financial intermediaries hoard labor, wages rise, leading to less labor and therefore lower output in the real sector, contemporaneously with the FLN shock. Lower output leads to lower investment as households are unwilling to substantially cut consumption. Going forward, output and investment continue to be low for two reasons. First, lower investment at the time of the shock leads to slower capital accumulation and lower future output. Second, because of lower lending, firms' capital structure is further away from optimal, leading to lower productivity and lower output.

Robustness

In the results above, we focus on bivariate regressions, comparing FLS to other predictors one at a time. In Appendix tables B.3, B.4, and B.5 we redo the results with multivariate regressions that include all predictors together. Although the danger of multicolinearity makes these results difficult to interpret, FLS remains significant in almost all specifications. The two exceptions are 1 year ahead equity predictability and 1 year ahead credit risk predictability, both of which keep the same sign, but become insignificant.

In all of our regressions, we have included aggregate labor share as a control, thus the results suggest that there is something unique to the labor share of financial intermediaries. As an additional placebo, we have constructed a labor share measure of high skilled workers, unfortunately, it is only available starting in 1997. In Appendix table B.6, we show that high skilled labor share does not predict any of our variables of interest. On the other hand, despite the shorter sample, financial sector labor share retains most of its predictive power.

[17] The negative contemporaneous correlation between FLS and GDP growth may raise concerns that the shock originates from firms and propagates to the financial sector. To alleviate this concern, we confirm that GDP growth does not Granger cause FLS, while FLS does Granger cause GDP growth at 10% significance.

Since FLS is a ratio, it may be interesting to know whether its predictability is due to the numerator (compensation) or the denominator (value added). Both the numerator and the denominator are non-stationary, therefore we cannot include both independently in the regression, instead, we include the growth of value added (ΔFVA) as one of the controls. For the equity premium, debt growth, and credit spread, inclusion of ΔFVA does not affect the predictive power of FLS. However, for GDP growth and investment growth, FLS becomes insignificant, suggesting for these two variables, most of the forecasting power comes from the denominator. Similarly, all of our bank and bank-firm results in Sections 2.2.2 and 2.2.3 below include earnings growth as a control.

Drivers of FLS

To understand the drivers of FLS, we use two methods to estimate aggregate disturbances to FLS in the data. In the first, we regress FLS on well-identified macro shocks in the literature including shocks to TFP, time-varying uncertainty, financial frictions, etc., and extract the shock to FLS. In the second, we estimate a VAR that includes several variables related to business cycles including GDP growth, aggregate labor share, wage growth, price-to-dividend ratio, credit spread and FI leverage (denoted by HKM) and again extract a shock to FLS.[18] We show these two shocks are highly correlated and drive 70-90% of the variation in FLS. This analysis shows that there is an aggregate shock that primarily drives the variation in FLS which is not captured by existing macro shocks documented in the literature. This is also the justification for why we introduce the FLN shock in the model.

The VAR exercise allows us to study how FLS respond to other macro variables. The impulse responses are shown in Appendix figure B.8. By far, the strongest response of FLS is to its own shock. The responses to all other shocks are not significantly different from zero.

We then recompute all of the aggregate results using each of these shocks rather than FLS as our key explanatory variable. We find that the results are mostly robust: excess return predictability is reduced at a one year horizon but remains significant at other horizons; debt and investment growth predictability remains strong at all horizons; credit spread and GDP growth predictability remains significant at shorter horizons.

[18] The sample for these two exercises are from 1970 to 2019. Results are available upon request.

Lastly, in the model presented in Section 3.2, FLS is positively associated with expected stock returns and credit spreads, and negatively with output, investment, and credit issuance, which is why FLS is our independent variable of interest. However, FLS is an endogenous variable in the model, mostly driven by the exogenous FLN shock – the shock to the labor needed per unit of capital by financial intermediaries (ν_b in the model). In the data, the FI labor to capital share is non-stationary, declining significantly during our sample, therefore we compute its 1-sided HP filter. This variable has a 0.63 correlation with FLS. In Appendix Tables B.7, B.8, B.9, B.10, B.11, and B.12 we show that it has quantitatively similar predictive power as FLS.[19]

Appendix Table B.16 also shows that the three alternative measures of the financial sector's labor burden used in this section (ν_b, and the two extracted shocks) co-move closely with FLS.

2.2.2 Bank-level analysis

In this section, analogous to the previous section, we explore the empirical relationships between bank level labor market fluctuations and firm level fluctuations in credit, credit risk, and real outcomes. We do so through panel regressions. Bank-level regressions significantly expand sample size and allow us to include more granular variables and fixed effects to control for other factors and the credit demand effect. We show that banks with higher FLS tend to lend less and have higher risk, as measured by EDF.

Data and variables definitions

For bank-level regression analysis, we focus on bank holding companies and use balance sheet variables from FR Y-9C, available from Federal Reserve Bank of Chicago. Following the literature, we apply several filters to select bank holding companies.[20] The final sample for bank-level analysis is a panel consisting of

[19]We use a filtering parameter of 100, standard for annual data. The reason we use FLS in our main results, rather than filtered FI labor to capital ratio, is that FLS is stationary over our sample, whereas for FI labor to capital, we would need to choose a filtering parameter, which is an additional degree of freedom.

[20]We drop observations with missing values or non-positive values for total assets; we keep bank holding companies (RSSD9331=28); we drop Grandfathered savings and loan holding company (RSSD9425=18); we drop lower-tier holding companies whose higher-tier also files Y-9C (BHCK9802=2); we keep holding company (RSSD9048=500), and exclude securities broker or dealer (RSSD9048=700), insurance broker or company (RSSD9048=550), utility company (RSSD9048=710), and other non-depository institution (RSSD9048=720) but keep Goldman Sachs, Morgan Stanley, Ally, and American Express. Finally, we drop observations with negative labor share.

41,511 annual observations in total, including 4,307 unique bank holding companies from 1986 to 2019.[21]

Our key independent variable is bank i's labor share, which is defined as the ratio of labor expenses to the sum of earnings before interest and labor expenses: $FLS_{i,t} = \frac{XLR_{i,t}}{EBIT_{i,t}+XLR_{i,t}}$, where XLR is the labor expenses and EBIT is the earnings before interest. The bank level dependent variables are the bank's average expected default frequency (EDF) over the next 3 years and the 3 year growth in total loans.[22] Bank holding company characteristics used as controls include bank size, return to assets, capital ratio, interest expense, earnings growth, and share of non-performing commercial and industrial (C&I) loans.[23] We also include bank holding company fixed effect α_i and its state-year fixed effect $\delta_{s,t}$, where s is for state and t is for year. The state-year fixed effect is used to control for local demand and other local shocks effect including changes in bank regulation. We estimate the following model:

$$y_{i,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}, \tag{2.1}$$

where $y_{i,t+k}$ is either bank i's 3 year loan growth or its 3 year credit risk.[24]

Bank FLS and bank loan growth

In this subsection, we examine the bank's loan growth over the next 3 years as the variable of interest $y_{i,t+k}$. Table 2.7 shows that a bank's labor share (FLS$_{i,t}$) negatively and significantly predicts total loan growth over the next 3 years (columns (1) to (4)), as well as C&I loan growth (columns (5) to (8)). The relationship is strong, with t-statistics ranging from -7.8 to -26.2, depending on the specification. The coefficient estimates in the first rows of column (4) and (8) imply that a one-standard-deviation increase in bank labor share

[21] The number of bank holding companies by year is shown in Appendix Figure B.1.

[22] These are items BHCK2122+BHCK2123. We also consider sub-components like C&I loans (BHCK1766); C&I loans to firms in U.S. (BHCK1763), consumer loans (BHCK1975) and real estate loans (BHCK1410).

[23] Size is measured as log of total asset (BHCK2170), return to assets is measured as ratio of net income (BHCK4340) to total assets (BHCK2170), capital ratio is measured as ratio of total equity to total assets, interest expense is measured as the ratio of total interest expense (BHCK4073) to total deposits (BHDM6631+BHDM6636+BHFN6631+BHFN6636), while share of non-performing C&I loan is measured as ratio of total non-performing C&I loan (BHCK1606+BHCK1607+BHCK1608) to total loan. Note that capital ratio is a measure of financial leverage for banks, similar to the leverage ratios that we use in the aggregate analysis.

[24] We define loan growth as $y_{i,t+k} = \Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k})-Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t+1:t+k})+Avg(Loan_{i,t-k+1:t})}$ and credit risk as $y_{i,t+k} = Avg(EDF_{i,t+1:t+k})$ where the forecast horizon is 3 years ($k = 3$).

reduces total loan growth and business loan growth rates by 25.3% and 36.2%.[25]

Bank FLS and bank credit risk

In this subsection, we examine the bank's credit risk, as measured by its average EDF over the next 3 years, as the variable of interest $y_{i,t+k}$.[26] Table 2.8 shows that a bank's labor share ($FLS_{i,t}$) positively and significantly predicts the bank's future credit risk, with t-statistics between 5.2 and 7.8, depending on the specification. The coefficient estimate in the last column implies that a one-standard-deviation increase in labor share increases EDF by 43.3%.[27]

2.2.3 Bank-firm pair analysis

In the previous subsection, we analyze how loan lending at the bank holding company level is affected by its labor share. However, if firms were to simply substitute their borrowing from affected to unaffected banks, then any effects on firms would be limited. On the other hand, if firms are "locked-in", as proposed by Sharpe (1990) and Rajan (1992b), and empirically tested by Chodorow-Reich (2014), then firms with relationships to affected banks would also be affected. Indeed, below we show that firms that are connected to affected banks by lending relationships issue less debt, pay higher prices for the debt they issue, have higher expected default probability, and have slower earnings growth. Although they do not invest significantly less on average, those firms that are financially constrained do invest significantly less.

Data and variables definitions

We study lender-borrower pairs at an annual frequency by using loan issuance data from Dealscan and combining it with firms' accounting data from Compustat.[28] We focus on syndicated loans, which are

[25]The standard deviation of FLS is 0.298, leading to 0.298*0.14=4.2% lower growth rates of total and business loans. The average 3 year growth rates are 16.6% and 11.6% respectively, therefore the reductions are 4.2/16.6=25.3% and 4.2/11.6=36.2%.

[26]Unlike the loan growth sample, this sample is from 1992 to 2011 due to data availability.

[27]The standard deviation of FLS is 0.273, leading to 0.273*1.44 = 0.39 higher EDF. The average EDF is 0.90, therefore the increase is 0.39/0.90 = 43.3%.

[28]WRDS has updated the Dealscan dataset starting from the summer of 2021. The update is a reorganization of the entire dataset, combining all the information in a single table and changing loan identifiers. The analysis here is based on a vintage of Dealscan, which is now considered the "legacy" version on WRDS. In particular, we use data from the following tables: Facility-Legacy, Package-Legacy, Company-Legacy, Lenders-Legacy, Current Facility

usually large loans with long maturities that are frequently issued by multiple lenders. For each syndicated loan, we only consider the lead lender's balance sheet and we use allocation information to determine lead lender's loan amount.[29]

Our key independent variable is the labor share of the lead lender i in year t ($FLS_{i,t}$). If the firm borrows multiple facilities from different lead lenders in a year, we use the weighted average (by loan amount) of lead lenders' labor share. We examine the effect of FLS on various firm level variables of interest $y_{i,j,t+k}$ where borrower j is borrowing from lender i in year t. We control for both lender and borrower's characteristics in the fixed effect regression specification:

$$y_{i,j,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k}, \tag{2.2}$$

where α_i is the bank fixed effect and $\delta_{s,t}$ is either the year or state-year or industry-year fixed effect. We include firm's state-year and 1-digit SIC-year fixed effects to address the concern that local economic conditions or industry conditions may affect firms' demand for loans.

The outcome variables $y_{i,j,t+k}$ we consider are firm j's growth in loan issuance over the next 3 years, average borrowing cost over the next 3 years, average distance to default over the next 3 years, change in investment rate over the next 3 years, or earnings growth over the next 3 years.[30,31] Firm characteristics

Pricing-Legacy and Dealscan-Compustat Linking Database.

[29] We apply the same filters to select bank holding companies as the ones used in the bank-level regression analysis, with additional details in Appendix section B.1.4. The merged sample contains 47 unique bank holding companies compared to 4307 in the full sample. The bank companies in the merged sample are larger ($18 billion versus $13 billion average size) and have higher FLS (0.67 versus 0.63), but are relatively similar in their ROE, leverage, capital ratio, and cost of funding.

[30] Loan issuance data from Dealscan is available at a quarterly frequency. We thus aggregate the amount of loan issuance every year for each bank-firm pair. We define issuance growth as $y_{i,j,t+k} = \Delta Loan\ Amount_{i,j,t+k} = 2\frac{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} - \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} + \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}$. We measure borrowing cost as as the weighted average (by loan amount) of loan spread "All-in-drawn" from Dealscan Loan Pricing dataset. We only consider facilities that use "LIBOR" as the base rate and drop facilities that have negative "All-in-drawn" or "All-in-drawn" over 1000 basis points. We drop facilities that have maturities shorter than one year. The borrowing cost is defined as $y_{i,j,t+k} = Avg(Loan\ Spread_{i,j,t+1:t+k})$. We follow Merton (1974) and Gilchrist and Zakrajšek (2012) to measure firm-level distance to default (D2D) and define $y_{i,j,t+k} = Avg(D2D_{t+1:t+k})$. Change in investment rate is defined as $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$. Earnings growth is defined as $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ where IB is Income Before Extraordinary Items. In all cases, the forecast horizon is 3 years ($k = 3$).

[31] To create a panel that is similar to a credit registry, we follow (Lin and Paravisini, 2013) for a modified approach of Khwaja and Mian (2008), sum the total amount of lending for each firm over subsequent three-year periods and use these aggregated loan amounts to compute the loan growth. Thus, when a new loan is initiated, we can compare the amount borrowed that year (and the following two years) to the amount borrowed in the three years prior to the new

used as controls include firm size, Tobin's Q, cash, financial leverage, past sales growth, tangibility and credit rating. Details about variable construction are provided in Appendix Table B.1.

The final sample for this pair panel regression analysis contains 17,907 bank-firm pair observations with 47 banks and 2709 firms from 1986 to 2019.[32] For bank-firm credit spread, we further merge the data with the loan pricing dataset, shrinking the sample to 15,601 bank-firm pair observations with 47 banks and 2342 firms. Summary statistics for bank holding companies are presented in Appendix Table B.13.

Bank FLS and firm credit outcomes

In this subsection, we examine the relationship between a bank's labor share (FLS) and various credit outcomes for firms connected to this bank. We find that firms connected to banks with high FLS borrow less, pay more to borrow, and have higher expected default rates. These results are presented in Table 2.9.

In Panel A, we investigate the growth rate of firm j's total loan borrowing over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively and significantly predicts the growth rate of loan issuance by firms that are connected to the bank through a lending relationship, with t-statistics ranging from -2.3 to -2.9, depending on the specification. The coefficient estimate of -0.51 in column (3) implies that a one-standard-deviation increase in a bank's labor share reduces new issuance of connected firms by 10.3%.[33]

In Panel B, we investigate firm j's borrowing cost over the next 3 years as the variable of interest $y_{i,j,t+k}$. A bank's labor share positively predicts the borrowing cost for firms that are connected to the bank through a lending relationship, although the statistical significance is marginal. The coefficient estimate of 0.33 in column (3) implies that a one-standard-deviation increase in a bank's labor share increases borrowing costs of connected firms by 5.0 bp or 3.0%.[34]

In Panel C, we investigate firm j's credit risk (measured as distance to default) over the next 3 years as the variable of interest $y_{i,j,t+k}$. A bank's labor share positively and significantly predicts the credit risk

loan. We follow an analogous strategy for other variables of interest.

[32]In our final sample, 95.6% of the firm-year observations have single lender, 4.3% of the firm-year observations have two lenders. We drop observations where firms have over three lenders in that period.

[33]The standard deviation of FLS is 0.156, leading to a 0.156*51% = 8.0% lower growth rate of loan borrowing. The average loan growth rate over 3 years is 78%, therefore this is a 8.0/78 = 10.3% reduction.

[34]The standard deviation of FLS is 0.153, leading to a 0.153*33 bp = 5.0 bp increase in the borrowing cost. The average borrowing cost is 169 basis points per year, and therefore, this is a 5.0/169 = 3.0% increase.

(negatively predicts distance to default) of firms that are connected to the bank through a lending relationship, with t-statistics between -2.8 and -3.8. The coefficient estimate of -1.61 in column (3) implies that a one-standard-deviation increase in a bank's labor share decreases the distance to default of connected firms by 3.9%.[35]

Bank FLS and firm real outcomes

In this subsection, we examine the relationship between a bank's labor share (FLS) and investment rate or earnings growth for firms connected to this bank. We find that firms connected to banks with high FLS experience lower earnings growth. They do not, on average, experience significant investment rate reductions, although the most financially constrained firms do reduce investment rate. These results are presented in Table 2.10.

In Panel A, we investigate the change of firm j's investment rate over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively but insignificantly predicts a lower investment rate for firms that are connected to the bank through a lending relationship, with t-statistics between -0.8 and -1.09. However, as we show in Appendix Table B.15, when we focus on financially constrained firms, defined as in the top tercile by their Whited and Wu (2006b) financial constraint index, the t-statistics rise to between -1.6 and -2.3 for constrained firms, while the point estimates are near zero for unconstrained. Since firms have other margins of adjustment – like using internal funds, borrowing from alternative lenders, or raising equity – it makes sense that financially constrained firms would be most affected.

In Panel B, we investigate the growth rate of firm j's earnings over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively and significantly predicts the growth rate of earnings by firms that are connected to the bank through a lending relationship, with t-statistics ranging from -2.1 to -2.4, depending on the specification. The coefficient estimate of -0.64 in column (3) implies that a one-standard-deviation increase in a bank's labor share reduces earnings growth of connected firms by 37.7%.[36] In Appendix Table B.15 we show that as with investment, the effect is much stronger for financially constrained

[35]The standard deviation of FLS is 0.156, leading to a -1.61*0.156 = -0.251 change in the distance to default. The average three-year distance to default is 6.46, and therefore, this is a -0.251/6.46 = 3.9% decrease in firm's credit risk.

[36]The standard deviation of FLS is 0.156, leading to a 0.64* 0.156 = 0.10 lower growth rate of earnings. The average earnings rate over three years is 26.5% and therefore, this is a 0.10/0.265 = 37.7% reduction.

firms, and near zero for unconstrained.

2.2.4 Direct evidence of FLN shocks

Most of this paper provides indirect evidence for FLN shocks by showing that high FLS is associated with credit market stress both at the aggregate and individual bank level. In this section we provide more direct evidence for one specific source of FLN shocks.

Using the same bank data as in Section 2.2.2, for each bank we instrument for FLS in one of two ways and present the results in Appendix Table B.17. First, we compute a time series of legal and data processing expenses; we consider it as a proxy for the bank's regulatory compliance burden. In the first stage, we instrument for the change in FLS by legal and data processing expenses scaled by total assets, the relationship is significant, this is in Column (1) of Panel A. In the second stage, we show that this instrument positively and significantly predicts the loan growth over the next three years, and negatively and significantly predicts the loan spreads on the bank's lending over the next three years. In Panel B, we do the same but using the aggregate change in financial industry regulatory burden as the instrumental variable.[37] Again, the instrument positively and significantly predicts loan growth and negatively and significantly predicts loan spreads.

In column (4) of Panel B we also show that the change in legal and processing expenses (the first instrument) is itself positively and significantly related to the aggregate increase in regulatory burdens. This is also consistent with survey evidence. For example, 49% of the respondents in an S&P Global Market Intelligence survey said compliance costs were up 20% or more since Dodd-Frank was implemented, and 59% said compliance costs now account for at least 10% of their annual expenses.

[37] To construct this measure, we follow Hogan and Burns (2019), who measure regulation burdens using the text of banks and banking regulation documents. More specifically, we use the number of regulatory restrictions, which captures the text of the Code of Federal Regulations Title 12 for language that restricts activities such as "shall" or "shall not" and "must" or "must not."

2.3 Model

In order to explain the empirical findings in section 2.2, we build a dynamic stochastic general equilibrium model in which banks intermediate between households, who invest capital, and corporations, who raise capital. The key mechanism in our model is that intermediation activities require banks to hire labor. The key shock in our model is a financial shock in the spirit of Jermann and Quadrini (2012b) and Khan and Thomas (2013),[38] but affecting the amount of labor needed per dollar of intermediated capital, we refer to these as FLN shocks.

In section 2.3.1 we write down a version of our model without banks or debt. We take this step because for tractability, we set up the firm's problem in a non-standard way and believe it is helpful for the reader to understand the simpler problem first. Typically in models with capital adjustment costs firms are infinitely lived, which requires the firms' problem to be solved numerically. In our model new firms are born each period and live until next period only, which allows us to solve the firm's problem analytically as a function of the state. In sections 2.3.2, 2.3.2, and 2.3.2 we write down the problem of the households, firms, and banks for the more general case with banks and corporate debt. We then desribe the calibration in section 2.3.3 and explain the results in section 2.3.4. Finally, in section 2.3.5, we explore alternative mechanisms and argue that it is difficult to explain the data without FLN shocks. In Appendix sections B.3.2 and B.3.3 we extend this model to have corporate default and wage rigidity.

2.3.1 Frictionless problem

Households have CRRA utility and supply a constant amount of labor N_t, normalized to one. Let NW_t be the household's net worth, $W_t N_t$ the wage multiplied by the labor supply (equivalently labor income), C_t its consumption, θ_t the shares of equity it owns ($\theta_t = 1$ in equilibrium), $V_{t,o}$ (o for old) the t equity value of firms born at $t-1$ who pay out their profit at t and then shut down, and $V_{t,n}$ (n for new) be the t equity value of firms born at t. For brevity, we do not include a risk free asset in this problem, though it will be available

[38] These papers model a financial shock to how collateralizable capital is.

in the full problem we write down further below. The household's problem is:

$$
\begin{aligned}
&U(NW_t) = \max_{C_t} \frac{C_t^{1-\rho}}{1-\rho} + \beta E_t\left[U(NW_{t+1})\right] \quad \text{s.t.} \\
&\theta_{t+1} V_{t,n} = NW_t + W_t N_t - C_t \\
&NW_{t+1} = \theta_{t+1} V_{t+1,o} \\
&N_t = 1.
\end{aligned}
\tag{2.3}
$$

At t, a measure one of new firms are born. New firms raise equity in amount $V_{t,n} = K_{t+1}Q_t$ and use it to purchase capital K_{t+1} at a price per unit Q_t. At the same time, old firms choose how much new capital S_t to create, pay adjustment costs associated with creation and installing new capital, sell their capital to new firms for S_tQ_t (in equilibrium $S_t = K_{t+1}$), sell their output, pay labor costs, pay the proceeds $V_{t,o}$ to their equity owners, and shut down. The new firms at t become old at $t+1$ and their value at $t+1$ is:[39]

$$V_{t+1,o} = Z_{t+1}K_{t+1}^{\alpha}N_{t+1}^{1-\alpha} - W_{t+1}N_{t+1} + K_{t+1}(1-\delta) - S_{t+1} - \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2 K_{t+1} + Q_{t+1}S_{t+1}. \tag{2.5}$$

In the above equation, investment is $S_{t+1} - K_{t+1}(1-\delta)$. If there were no adjustment costs ($\nu_{k,0}$=0), then $Q_t = 1$ and the value of the old firm at $t+1$ is simply the value of output plus undepreciated capital: $V_{t+1,o} = Z_{t+1}K_{t+1}^{\alpha}N_{t+1}^{1-\alpha} - W_{t+1}N_{t+1} + K_{t+1}(1-\delta)$. With adjustment costs, firms who sell S_{t+1} units of new capital lose the capital itself, plus disassembly costs $\nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2$. The investment decision is orthogonal to the production decision, therefore all firms with undepreciated capital will make identical investment decisions and their FOC for investment implies:

$$Q_t = 1 + 2\nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right). \tag{2.6}$$

[39]Firms take wages as given and make identical labor decisions, their FOC for labor implies $W_t = (1-\alpha)Z_t\left(\frac{K_t}{N_t}\right)^{\alpha}$ and $N_t = \left(\frac{(1-\alpha)Z_t}{W_t}\right)^{\frac{1}{\alpha}}K_t$. Define $X_t = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}W_t^{\frac{\alpha-1}{\alpha}}Z_t^{\frac{1}{\alpha}} = \alpha Z_t\left(\frac{K_t}{N_t}\right)^{\alpha-1}$, which depends only on aggregate quantities Z_t and W_t (alternatively, on aggregate Z_t, K_t, and N_t) so the firm takes it as given. Equation 2.5 can therefore be rewritten as as:

$$V_{t+1,o} = X_{t+1}K_{t+1} + K_{t+1}(1-\delta) - S_{t+1} - \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2 K_{t+1} + Q_{t+1}S_{t+1}. \tag{2.4}$$

In Appendix section B.3.1 we show that the solution to this problem with overlapping generations of firms is identical to the standard Q-theory problem with infinitely lived firms who pay capital adjustment costs.

2.3.2 Full model

We next extend the above model to include banks who raise deposits from households and lend riskless corporate debt to firms. The key mechanism is that the intermediary services that banks engage in require banks to hire labor, and the cost of providing these services varies over time. In Appendix section B.3.2 we extend the model to allow default by firms, although the channel we are interested in works even with riskless debt. In Appendix section B.3.3 we extend the model to allow for wage rigidity. The overlapping generation modeling assumption makes these extensions computationally tractable because we can solve the firm's problem analytically.

Households

Households are identical to the specification above, with the following differences: i) households can invest in risk free bank deposits with face value $B_{t+1,d}$ and interest rate $R_{t,d}$, ii) households can invest in bank equity, iii) households receive a liquidity benefit from investing in deposits, iv) households pay an equity issuance cost increasing in the size of corporate equity issuance. We assume that banks hold corporate debt while households do not. The household's problem is now written as:

$$\begin{aligned}
&U(NW_t) = \max_{C_t, B_{t+1,d}} \frac{C_t^{1-\rho}}{1-\rho} + \beta E_t \left[U(NW_{t+1})\right] \quad \text{s.t.} \\
&\theta_{t+1,c} V_{t,cn} + \theta_{t+1,b} V_{t,bn} + B_{t+1,d}/R_{t,d} = NW_t + W_t N_t - C_t + \Lambda\left(\frac{B_{t+1,d}}{R_{t,d}}\right) - \Upsilon\left(\frac{\theta_{t+1,c} V_{t,cn}}{K_{t+1} Q_t}\right) \\
&NW_{t+1} = \theta_{t+1,c} V_{t+1,co} + \theta_{t+1,b} V_{t+1,bo} + B_{t+1,d} \\
&N_t = 1,
\end{aligned} \tag{2.7}$$

where $V_{t,cn}$ and $V_{t,bn}$ are the values of a new productive firm and a new bank that begin operating at t, $V_{t+1,co}$ and $V_{t+1,bo}$ are the values of an old productive firm and an old bank who shut down at $t+1$, and $\theta_{t+1,c}$ and $\theta_{t+1,b}$ are the number of shares of corporate equity and bank equity purchased by households. The function

$\Lambda(x) = \lambda_0 x^{\lambda_1}$ specifies the liquidity benefit of deposits.[40] The function $\Upsilon\left(\frac{\theta_{t+1,c}V_{t,cn}}{K_{t+1}Q_t}\right) = \upsilon_0\left(\frac{\theta_{t+1,c}V_{t,cn}}{K_{t+1}Q_t}\right)^{\upsilon_1}$ specifies the cost of investing in corporate equity.[41]

The household's stochastic discount factor is $M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\rho}$. The returns on productive firms equity and bank equity are, respectively, $R_{t+1,c} = \frac{V_{t+1,co}}{V_{t,cn}}$ and $R_{t+1,b} = \frac{V_{t+1,bo}}{V_{t,bn}}$. The Euler equations for productive firm equity, bank equity, and deposits are:

$$
\begin{aligned}
&1 = E_t[\widehat{M}^c_{t+1}R_{t+1,c}] \quad \text{where } \widehat{M}^c_{t+1} = M_{t+1}\left(1+\upsilon_0\upsilon_1\left(\frac{\theta_{t+1,c}V_{t,cn}}{K_{t+1}Q_t}\right)^{\upsilon_1-1}\frac{1}{K_{t+1}Q_t}\right)^{-1} \\
&1 = E_t[M_{t+1}R_{t+1,b}] \\
&1 = E_t[\widehat{M}^d_{t+1}R_{t+1,d}] \quad \text{where } \widehat{M}^d_{t+1} = M_{t+1}\left(1-\lambda_0\lambda_1\left(B_{t+1,d}/R_{t,d}\right)^{\lambda_1-1}\right)^{-1}.
\end{aligned} \tag{2.8}
$$

The last term in the $\widehat{M}^c_{t+1}$ equation reflects equity issuance costs, while the last term in the $\widehat{M}^d_{t+1}$ equation reflects the liquidity benefit of deposits.

Productive firms

Firms are similar to the firms described in section 2.3.1, except that they can raise both riskless debt and equity to finance purchases of capital, and their output is reduced when deviating from an optimal quantity of debt.[42]

At t, a firm raises equity in amount

$$V_{t,cn} = K_{t+1}Q_t - B_{t+1,cd}/R_{t,cd}. \tag{2.9}$$

The firm's equity value at $t+1$ is similar to before, however it now owes creditors $B_{t+1,cd}$, and its output is

[40] The liquidity benefit gives banks a reason to exist. In our model, banks have an additional reason to exist because firms with too little debt are less productive, and banks are the only way for firms to borrow. Therefore, we do not need the liquidity benefit for our model to work. However, if we were to shut down the optimal capital structure channel, we would need the liquidity benefits for banks to exist. An alternative to our modeling choice would be to put the liquidity benefit in the utility function rather than the budget constraint. We conjecture it would not affect our main result relating FLS to lending, output, and asset prices.

[41] These costs can arise either from direct transaction costs (e.g., flotation costs) or costs associated with information asymmetries or managerial incentive problems.

[42] There are several corporate finance theories that could be used to justify this last assumption. For example, having too little debt increases the need for outside equity and may reduce incentives of insiders. Having too much debt may lead to increased distress costs.

affected by the quantity of debt.

$$\begin{aligned} V_{t+1,co} &= Z_{t+1}\left(\Psi_{t+1}K_{t+1}\right)^{\alpha} N_{t+1,c}^{1-\alpha} - N_{t+1,c}W_{t+1} \\ &\quad + K_{t+1}(1-\delta) - S_{t+1} - \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2 K_{t+1} + Q_{t+1}S_{t+1} - B_{t+1,cd}, \end{aligned} \tag{2.10}$$

where $\Psi_{t+1} = 1 - \nu_{cd,0}\zeta_t^2$ reflects the reduction in a firm's productivity due to having too much or too little debt. Ψ_{t+1} is a function of $\zeta_t = \frac{B_{t+1,cd}/R_{t,cd}}{K_{t+1}} - \nu_{cd,1}$, which is the distance between the firm's debt-to-capital ratio, and its optimal debt-to-capital ratio $\nu_{cd,1}$.[43] We designate $N_{t,c}$ as the employment in the productive (corporate) sector, as opposed to financial sector employment $N_{t,b}$, and total employment $N_t = N_{t,c} + N_{t,b}$.

The firm's investment decision is identical to before: $Q_{t+1} = 1 + 2\nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)$. The firm takes the corporate interest rate as given. The firm's capital structure decision is independent of the investment decision – the firm chooses debt to maximize expected cashflows to equity holders $-V_{t,cn} + E_t[\widehat{M}_{t+1}^c V_{t+1,co}]$.[44] The choice of debt therefore satisfies:

$$1 - E_t[\widehat{M}_{t+1}^c]R_{t,cd} = 2\nu_{cd,0}\left(\frac{B_{t+1,cd}/R_{t,cd}}{K_{t+1}} - \nu_{cd,1}\right)E_t[\widehat{M}_{t+1}^c X_{t+1}]. \tag{2.12}$$

The above equation is intuitive. When the return on corporate debt is fairly priced from the point of view of the firm, then the left hand side is zero and leverage $\frac{B_{t+1,cd}/R_{t,cd}}{K_{t+1}}$ is equal to its target $\nu_{cd,1}$. On the other hand, when the interest rate is especially high (low) then the left hand side is negative (positive) and leverage is chosen below (above) target.

Banks

At t, new competitive banks are born who will live for one period. At t, they raise equity capital $V_{t,bn}$ and deposits $B_{t+1,d}/R_{t,d}$, pay labor costs $N_{t,b}W_t$, and lend all of their remaining capital to firms, with total lending being $B_{t+1,cd}/R_{t,cd}$. Note that $B_{t+1,d}$ and $B_{t+1,cd}$ are, respectively, the $t+1$ face values of deposits

[43] By solving for the firm's optimal labor choice, the problem can be rewritten as:

$$\begin{aligned} V_{t+1,co} &= X_{t+1}\Psi_{t+1}K_{t+1} + K_{t+1}(1-\delta) - S_{t+1} - \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2 K_{t+1} + Q_{t+1}S_{t+1} - B_{t+1,cd} \quad \text{s.t.} \\ X_t &= \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} W_t^{\frac{\alpha-1}{\alpha}} Z_t^{\frac{1}{\alpha}}. \end{aligned} \tag{2.11}$$

[44] Equation 2.8 implies that this quantity is zero in equilibrium since equity is fairly priced

and corporate debt. At $t+1$, banks collect revenue from corporate lending, pay off depositors, pay the remainder of their capital to equity holders, and then shut down. At $t+1$, a new set of competitive banks are born.[45]

Deposits raised by banks provide liquidity, and therefore have a lower rate of return than the risk free rate. Equation 2.8 shows that they are also a cheaper (risk adjusted) source of financing than bank equity: $E_t[M_{t+1}R_{t,d}] \le E_t[M_{t+1}R_{t+1,b}] = 1$. For this reason, all else equal, banks would maximize deposit financing and minimize equity financing. Banks face a capital constraint κ, limiting the ratio of deposits to equity:

$$B_{t+1,d}/R_{t,d} = \kappa V_{t,bn}. \tag{2.13}$$

The labor needed to intermediate capital is proportional to the bank's capital, with the proportionality constant $\nu_{b,t}$ subject to shocks – these FI labor need (FLN) shocks are the focus of our study:

$$N_{t,b} = \nu_{b,t}\left(V_{t,bn} + B_{t+1,d}/R_{t,d}\right) = \nu_{b,t}(1+\kappa)V_{t,bn}. \tag{2.14}$$

Equation 2.14 represents the bank's production function and FLN shocks are technology shocks to the production of intermediation, with production becoming more expensive when $\nu_{b,t}$ is high. They can be thought of as a reduced form way to model intermediary behavior in a changing investment environment. As we will show in section 2.3.5 below, we identify the FLN shock by matching the countercyclical behavior of the fraction of FI labor in the aggregate employment, which is hard to generate in other models without the FLN shock.

A bank that has raised equity capital $V_{t,bn}$, chooses deposits $B_{t+1,d}/R_{t,d}$ based on equation 2.13, pays labor costs in amount $W_t N_{t,b}$ with $N_{t,b}$ from equation 2.14, and invests a total of:

$$\begin{aligned} B_{t+1,cd}/R_{t,cd} &= V_{t,bn} + B_{t+1,d}/R_{t,d} - W_t N_{t,b} \\ &= V_{t,bn}(1+\kappa)(1-\nu_{b,t}W_t). \end{aligned} \tag{2.15}$$

[45]The standard FI asset pricing channel works by having banks suffer negative shocks, leading to low equity valuations, and causing them to contract balance sheets. This channel is dynamic. Because our banks live for two periods, that channel is absent by construction. One could reintroduce it either by having time-varying equity issuance costs, leading to low bank equity in some periods, or by linking banks intertemporary, for example by having the new bank's equity issurance at $t+1$ be a function of the old bank's dividend payout at $t+1$.

The bank's payout at $t+1$ is:

$$\begin{aligned} V_{t+1,bo} &= B_{t+1,cd} - B_{t+1,d} \\ &= V_{t,bn}\left((1+\kappa)(1-\nu_{b,t}W_t)R_{t,cd} - \kappa R_{t,d}\right). \end{aligned} \tag{2.16}$$

From the firm's problem, we can solve for $R_{t,cd}$ as a function of $B_{t+1,cd}$, it falls when $B_{t+1,cd}$ is too large as firms refuse to take on additional debt unless it is very cheap. Similarly, from the household's problem, we can solve for $R_{t,d}$ as a function of $B_{t+1,d}$, it rises when $B_{t+1,d}$ is too large as households have lower marginal utility from additional deposits. Thus, banks are very profitable (per unit of capital) when bank assets are low, and unprofitable when bank assets are high. In equilibrium, the size of the bank's balance sheet (or equivalently, its equity value) will adjust in order to make the Euler equation hold: if $V_{t,bn}$ is too low (high) then the bank will be very profitable (unprofitable) and $E_t[M_{t+1}R_{t+1,b}]$ will be above (below) one.

Equilibrium

Total demand for equity shares are $\theta_{t+1,b} = \theta_{t+1,c} = 1$. Labor market clearing implies that $N_{t,c} = 1 - N_{t,b}$. Starting with the household's budget constraint and substituting in the definitions of productive firms equity and bank equity, one can compute the aggregate budget constraint.

$$\begin{aligned} C_t &= Z_t\left(1-\nu_{cd,0}\left(\frac{B_{t,cd}/R_{t-1,cd}}{K_t} - \nu_{cd,1}\right)^2\right)K_t^{\alpha}(1-N_{t,b})^{1-\alpha} \\ &\quad +(1-\delta)K_t - K_{t+1} - \nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t + \Lambda(B_{t+1,d}/R_{t,d}) - \Upsilon\left(\frac{\theta_{t+1,c}V_{t,cn}}{K_{t+1}Q_t}\right). \end{aligned} \tag{2.17}$$

On the right hand side in the equation above, the first line is aggregate output minus reductions due to deviations from target leverage; the second line is investment, capital adjustment costs, liquidity from deposits, and equity issuance costs. The equilibrium consists of household policies for consumption C_t and investment $\theta_{t+1,c}$, $\theta_{t+1,b}$, $B_{t+1,d}$; firm policies for investment S_t and borrowing $B_{t+1,cd}$; as well as prices $V_{t,cn}$, $V_{t,bn}$, W_t, $R_{t,cd}$, $R_{t,d}$ such that the household's Euler equations are satisfied, the firm's optimality conditions for investment and borrowing are satisfied, and the aggregate budget constraint is satisfied. Appendix section B.3.5 describes the solution method.

2.3.3 Calibration

The model is calibrated annually. This subsection describes the parameter choices, which are listed in Table 2.11. The top panel of this table presents parameters associated with the model's business cycle dynamics, which are relatively standard in the literature. Specifically, the time discount factor β is 0.98, the risk aversion ρ is 2, the share of capital in production α is 0.35, the depreciation rate δ is 0.064, and the growth rate of TFP g is 0.018. The capital adjustment cost function is such that in steady state, when $K_{t+1} = (1+g)K_t$, the cost paid is zero. The strength of the capital adjustment cost is chosen to approximately match the ratio of the volatility of investment growth to output growth in the data; the actual cost paid is 0.24% of output on average. The above model implies a capital to output ratio of 2.6, in line with the data. The top panel in Table 2.12 shows that consumption and investment in the model are similar to the data in terms of their size relative to output, their volatility, and their co-movement with output. The TFP shock grid is chosen to approximately match the volatility of private output growth in the data, it is 0.037 in the model, compared to 0.035 in the data for 1949-2021, and 0.051 for 1929-2021.

The bottom panel of this Table 2.11 presents moments specific to our channel. The key variable in our model is the FI's labor to asset ratio $\nu_{b,t}$. We choose its mean to be 0.018 to match the labor share of financial intermediaries; this quantity is 0.64 in the data and our model.[46] The grid for $\nu_{b,t}$ (FLN shocks) is chosen to approximately match the volatility of financial employment share as a fraction of total employment,[47] this quantity is 0.006/0.055=0.11 in the data and 0.10 in the model.

The model has two exogenous shocks, a TFP shock Z_t and an FLN shock $\nu_{b,t}$. The TFP shock has a non-stationary, deterministic component $(1+g)^t$ and a stationary, random component, while the FLN shock is stationary. Each stationary shock is Markov and takes on one of three values, shown in Table 2.11, implying a Markov chain of $3^2 = 9$ possible states for the random shock. Our goal in choosing the transition probability matrix is to approximately match the autocorrelation of HP-filtered private output, which is 0.33 in the data (1949-2021), the autocorrelation of HP-filtered $\nu_{b,t} = \frac{N_{t,b}}{V_{t,bn}+B_{t+1,d}/R_{t,d}}$, which is 0.50 in the data

[46] Alternately, we could have used $\nu_{b,t}$ to target the financial sector's employment share as a fraction of total employment. We do not do this for the following reason. In the data, financial sector employment share is approximately 5.5% of total employment, in our model, it is 3.6%. However, in our model, the financial sector intermediates only debt issuance by the productive sector, while in the real world the financial sector also intermediates mortgages and some purchases of corporate equity.

[47] $\sigma(x)/\mu(x)$ where x is financial employment as a share of total.

(1951-2021), and the correlation of HP-filtered private output with HP-filtered $\nu_{b,t}$, which is -0.23 in the data (1951-2021). Appendix section B.3.4 describes how we choose the transition probability matrix. In the model, the three quantities are 0.24, 0.42 and -0.36.

The remaining moments matter for modeling banks who borrow from households and lend to firms. While these affect the model quantitatively, they are not crucial for our channel. The maximum ratio of FI debt to equity κ is 4, in the data this quantity is 4.3.[48] The curvature of the liquidity function λ_1 is 0.5, it must be below one in order for the household's demand function to be increasing in the deposit rate. The strength of the liquidity function λ_0 is 0.025, which implies a liquidity premium of 100bp for deposits relative to the risk free rate.[49] The target debt to capital ratio $\nu_{cd,1}$, at which trade-off theory costs and benefits cancel out, is 0.5, while the strength of the cost for deviating $\nu_{cd,0}$ is 0.05. We chose these parameters jointly to target a corporate debt to enterprise value ratio of 0.4.[50]

We do not have guidance from the literature as to the best way to model equity issuance costs, since they include both direct transaction costs and indirect costs associated with symmetric information and agency. We choose the strength of the equity issuance cost $\upsilon_0 = 0.35$ to target the Sharpe ratio of the aggregate stock market return, it is 0.41 in the data and 0.36 in the model. We choose the curvature of the equity issuance cost $\upsilon_1 = 8$ to match the increase in the expected market equity premium when the financial sector labor share rises. In the data, a one standard deviation increase in the financial sector labor share is associated with the expected equity premium over the next year rising by a factor of 1.27, and the equity premium over the next two years rising by a factor of 1.44, in the model these are 1.25 and 1.20. The actual cost paid is small, less than 0.2% of equity value on average, and 0.4% of equity value maximum.

The bottom panel of Table 2.12 presents selected asset pricing moments. The equity return is only about 1/3 as volatile as in the data, this is a problem common to asset pricing models unless some additional

[48] In the Integrated Macro Accounts, the average $\frac{\text{debt securities + loans}}{\text{market equity + debt securities + loans}}$ for 1960-2019 is 0.73, implying $\kappa = 4.3$.

[49] The only risk free asset available to households in the model is deposits, which are bundled with liquidity services. We can use the stochastic discount factor to compute the hypothetical risk free rate. The analog in the data is the spread between the Fed Funds rate and bank deposits. Drechsler et al. (2017b) show that this spread varies significantly across the business cycle, and across different types of deposits. Based on their Figure 1, the average spread 1997-2013 is -1.2% for time deposits, 1.3% for saving deposits, and 3.4% for checking deposits; however it is near zero when rates are low, and much higher when rates are high. We target 100bp as a conservative estimate, although our key results are not significantly different with a higher spread.

[50] The same debt to value ratio can arise in a model with a higher (lower) $\nu_{cd,1}$ combined with a lower (higher) $\nu_{cd,0}$. We do not attempt to identify each of these parameters independently.

mechanism to increase equity volatility is included, however the Sharpe ratio is comparable to the data.[51] The premium on corporate bonds over deposits is also about 1/3 that of the data. The deposit rate is relatively smooth, as in the data, though it is higher than the data. The high average deposit rate is a reflection of the low equity premium.

2.3.4 Results

Figure 2.1 presents impulse responses to an FLN shock, showcasing our main results: an FLN shock is associated with an increase in FI labor share, and in FI templyoment share of total employment. It is also associated with lower current and future output, investment and lending; higher current and future credit spreads; lower current stock returns, and a higher future equity premium. These are exactly the patterns documented for the data in section 2.2.[52]

To produce this figure, we first simulate the model for 50 periods but forcing both productivity Z_t and FLN $\nu_{b,t}$ to be neutral; $t = 0$ in the figure is the last such period. At $t = 1$, $\nu_{b,t}$ (the quantity of labor that intermediaries need per dollar of assets) rises unexpectedly, while the productivity shock remains neutral. After $t = 1$, the productivity shock remains neutral, while the FLN shock is allowed to vary randomly, as governed by the calibrated Markov transition probability. After $t = 1$, the lines in this figure represent averages over many random draws of the $\nu_{b,t}$ shock. We scale all quantities by their values at $t = 0$.

Upon impact of the shock, the FI's labor share rises, peaks at $t = 2$, and continues to remain high for about 6 years. The labor share is defined as compensation divided by compensation plus value added.[53] The labor share rises because intermediaries need to hire more labor per dollar of capital. In principle, the

[51]For example adding habit, as in Chen (2017), wage rigidity, as in Favilukis and Lin (2015), or depreciation shocks, as in (Gomes and Michaelides, 2007) can increase equity volatility. Despite low risk aversion, the Sharpe ratio is high due to equity issuance costs υ_0.

[52]Although we do not explore the implications of FI heterogeneity in our model, the same result should hold for individual FIs and the firms that are connected with FIs. In particular, if banks face idiosyncratic FLN shocks that raise their labor needs and labor costs, they will require more labor to intermediate capital, and hence banks' labor share will rise and their lending will fall. Furthermore, this effect will transmit to the real sector. If firms face switching costs when choosing their lenders, firms connected to the affected banks will cut investment and reduce output. This mechanism will be consistent with the cross-sectional result that we document in section 2.2.2.

[53]We define value added as the net cash flow paid to the FI's equity investors. This is revenue from lending to corporations, minus costs of repaying deposits, minus issues of FI equity. The last component is important because in our model, intermediaries live for just one period, thus, without subtracting issues of FI equity, this calculation would yield a gross return on FI equity, whereas the value added is analogous to a net return.

labor share could fall if wages fell sufficiently, however the change in wages is relatively small. This is because, as shown in footnote 39, the aggregate wage is derived from labor demand in the productive sector $W_t = (1-\alpha)Z_t \left(\frac{K_t}{N_{t,c}}\right)^{\alpha}$. In this equation, the only variable that depends on FI labor demand is $N_{t,c} = 1 - N_{t,b}$. Since FIs hire approximately only 5% of the labor force, even large moves in FI labor $N_{t,b}$ have a relatively small (in percentage terms) effect on productive sector labor $N_{t,c}$, and therefore a relatively small effect on the aggregate wage.

Because it becomes more expensive to operate, intermediaries contract their balance sheets and cut lending. Corporate lending falls by 6% on impact, and remains low for the subsequent 8 years. Corporate interest rates rise by about 50 bps and remain high for the subsequent 6 years. This happens because reduced lending pushes firms further away from their optimal capital structure and they are willing to pay more to raise debt capital; at the same time, intermediaries need the higher spreads in order to pay for higher labor costs.

Output and investment fall by 0.4% and 2% on impact and remain low for the subsequent 10 years. Output falls for several reasons. First, the contraction in corporate lending causes firms to be further away from their optimal capital structure, which makes them less productive. Second, because intermediaries' balance sheets do not contract by as much as the increase in FI labor, overall FI labor demand rises, leading to an increase in the FI employment share of total employment, and leaving less labor available for the productive sector. In our model, aggregate labor is fixed, but this channel is likely relevant for the real world: Figure 2.3 and the bottom panel of Table 2.12 confirm that in the data, FI employment share of total employment goes up in bad times (Appendix figure B.2 makes this especially clear through a scatter plot). Third, investment falls, leading to a lower capital stock, which further lowers output. Investment falls for two reasons. First, households wish to smooth consumption and the initial fall in output requires a fall in investment to avoid a fall in consumption. Second, going forward, firms become less productive and less profitable, reducing incentives to invest.

At $t = 1$, the realized equity premium falls concurrently with the realization of the FLN shock. Going forward, the expected equity premium rises and remains elevated for about 6 years. The reason for the increased expected equity premium is that as banks cut lending in response to higher labor costs, firms are forced to substitute toward equity issuance. However, equity issuance costs are convex, thus raising additional equity becomes increasingly expensive. The elevated equity premium is necessary to compensate households for increased equity issuance costs.

2.3.5 How important are FLN shocks?

In this section we show that neither TFP shocks alone (without FLN shocks) nor alternative mechanisms like credit risk, wage rigidity, credit shocks, or labor adjustment costs are able to produce the same patterns as in our baseline model and as we document in the data. First, while it is possible to qualitatively produce some of the patterns in Figure 2.1 using alternative mechanisms, the quantitative responses of lending and credit spread are much weaker. Second, these alternative mechanisms imply that financial sector employment share as a fraction of total employment should fall in bad times, however it rises in our baseline model. Figure 2.3, figure B.2, and the bottom panel of Table 2.12 show that it also rises in the data; Table B.16 shows that it is strongly correlated with various measures of financial industry labor burden used in our empirical analysis; Table B.18 shows that this is unlikely to be driven simply by high human capital. Third, we carry out an exercise similar to Jermann and Quadrini (2012b) to show that FLN shocks significantly improve the model's ability to quantitatively match the data time series for several quantities of interest.

TFP versus FLN shocks

Figure 2.2 presents model impulse responses to a TFP shock. The responses of output and investment are much bigger than to a labor demand shock because TFP shocks in the model are the main driver of output fluctuations and are calibrated to match the volatility of output. However, FLS actually falls, rather than rises, meaning that a model with TFP shocks alone cannot explain the empirical findings in section 2.2 – low output and investment are associated with low, rather than high FLS. The reason that FLS falls is that after a negative TFP shock, the financial sector's value added rises significantly because the interest rate on corporate debt rises.[54]

To highlight the quantitative importance of FLN shocks, we carry out an exercise similar to Jermann

[54] Although the interest rate on corporate debt rises, the deposit rate rises by even more, leading to a rise in the corporate spread. Despite this, value added rises because a bank's value added is defined as total corporate lending multiplied by the interest on corporate debt, minus total deposits multiplied by the deposit rate, minus total bank equity issued. The last component is not multiplied by any rate.

and Quadrini (2012b). First, we compute an annual time series of actual TFP in the data for 1948-2020.[55] Similarly, we compute a time series of FLN in the data by dividing financial sector employees by the total liabilities and equity of the financial sector.[56] We then HP filter each series; as discussed in section 2.3.3, the two are negatively correlated. Finally, we discretize each HP filtered series so that we can use the values as shocks to Z and ν_b in the model.[57]

We simulate the baseline model for 1000 periods while setting both shocks to their means in order to let the model reach its stochastic steady state. We then simulate the model for 73 additional periods, with each period corresponding to a year between 1948 and 2020. For each of these years, we set both the TFP and FLN shocks to be the discretized HP filtered values computed in the data. For comparison, we also solve a model with TFP shocks only, setting the FLN shocks to be their mean value. For each of these two simulations, table 2.13 reports the correlation between model implied and actual quantities of interest.

In the model with TFP shocks alone, both GDP and investment behave much as they do in the data, with correlations of 0.44 and 0.46, respectively. Adding FLN shocks leads to only a modest improvement, with the correlations rising to 0.45 and 0.49. The reason the improvement is modest is that TFP shocks in the model are calibrated to match output volatility and do most of the work for driving output and investment fluctuations. If we were to write down a model with a stronger link between credit and output, for example by adding explicit credit constraints or a working capital constraint, then FLN shocks would likely play a stronger role.

On the other hand, the model with TFP shocks alone cannot reproduce the actual patterns for debt growth, credit spread, and financial sector employment share, with correlations of 0.17, -0.11, and -0.08, respectively. On all of these dimensions, including FLN shocks in the simulation leads to a large improvement, with correlations rising to 0.33, 0.15, 0.51.

[55] We construct this series as $TFP_t = \frac{GDP_t}{K_t^\alpha \hat{N}_t^{1-\alpha}}$ where capital K_t is the historical cost net stock of private fixed assets, equipment, structures, and IP from BEA table 2.3 and $\hat{N}_t$ is the trend in hours, computed by regressing hours worked (FRED series B4701C0A222NBEA) on a time dummy. This is somewhat differerent from the standard computation of $TFP_t = \frac{GDP_t}{K_t^\alpha N_t^{1-\alpha}}$ because labor supply is inelastic in our model. The correlation between this series and TFP constructed by (Fernald, 2014), both HP filtered, is 0.74.

[56] These are FRED series USFIRE and FBLIEQQ027S.

[57] As discussed in section 2.3.3, Z and ν_b each take on three values – low, medium, and high – with unconditional probabilities $(0.28, 0.44, 0.28)$ for Z and $(0.175, 0.65, 0.175)$ for ν_b. To discretize the shocks, we choose cutoffs in real world data such that the low, medium, and high realizations have the same frequency as in the model.

Credit risk

In Appendix section B.3.2 we solve a model with FLN shocks and credit risk. In this model, as in the data, defaults rise when there is a negative TFP shock. This fixes the problem of value added rising in bad times, which was discussed in the previous section and is unrealistic. In this model, higher defaults lead to a fall in value added and a rise in labor share after a negative TFP shock. Figure B.3 shows that impulse responses to an FLN shock look qualitatively similar to our baseline model (without credit risk), although the responses of investment, corporate lending, and price of capital are all about 50% larger than in the baseline model (Figure 2.1). Therefore, the realistic addition of credit risk only strengthens our channel.

Figure B.4 shows that in the model with credit risk, most of the impulse responses to a TFP shock look qualitatively like the impulse responses to an FLN shock: FLS rises; output, investment, and lending fall; credit spreads rise; the equity return falls on impact but the expected equity premium rises. However, quantitatively, the change in lending and credit spreads is approximately one quarter that of the FLN shock. Furthermore, the increase in FLS lasts for just one period and then falls because expected returns on corporate debt rise. More importantly, TFP shocks imply that financial sector employment share as a fraction of total employment falls in bad times, however it rises after FLN shocks and in the data. Therefore, adding credit risk to the model makes the behavior of value added more realistic and does not diminish the importance of FLN shocks. However, as in our baseline model, TFP shocks alone cannot reproduce the patterns in the data.

Wage rigidity

If FI wages are especially rigid, then a high financial labor share would potentially indicate stress in credit markets even without an FLN shock. This is because after a negative shock to productivity, intermediaries would be unable to lower their wages by much due to rigidity, leading to higher labor expenses. This would in turn lead to a contraction in FI activities for the same reason as an increase in labor needs does in our baseline model.

In Appendix section B.3.3 we extend the model to have downward wage rigidity in the financial sector. Therefore, following a negative TFP shock, financial sector wages do not fall as fast as aggregate wages. For clarity, we shut down the FLN shock by setting $\nu_{b,t}$ to be constant (at its mean value), thus the only exogenous shocks to the model are TFP shocks. We focus on the model with credit risk because in the model without credit risk, value added counterfactually rises following a negative TFP shock, as discussed in section 2.3.5.

Appendix figure B.5 compares impulse responses to a TFP shock in a model without wage rigidity to one with wage rigidity in the financial sector. Consistent with the intuition above, compared to no wage rigidity, the model with wage rigidity has more positive impulse responses for financial sector labor share and aggregate credit risk; more negative impulse responses for output, investment, and corporate lending. However, quantitatively, the effects are small. For example after a TFP shock, the corporate spread rises by 2% more in a model with rigidity compared to one without; corporate lending falls by 1% more in a model with rigidity compared to one without. The FLN shock causes much bigger responses: a 21% rise in the spread and a 6% fall in lending. The effect of rigidity on the responses of output and investment are even smaller. Finally, as with TFP shocks, financial sector employment share as a fraction of total employment falls after a TFP shock, and falls by even more when wages are rigid. Therefore, even though wage rigidity can lead to qualitatively similar effects as an FLN shock, it is difficult for wage rigidity to matter much quantitatively and wage rigidity cannot explain the behavior of financial sector employment.

An opposite concern may be that if FI wages are much more flexible than other industries, then it would be relatively easy for FIs to keep their labor in bad times, explaining the strong counter-cyclicality of financial sector employment share as a fraction of total employment. We find that this is unlikely to be the case because FI wages appear to be more rigid than other sectors.[58]

Labor adjustment costs

Here we argue that labor adjustment costs also cannot reproduce the same patterns as in the data.

First, as discussed earlier, the FI employment share of total employment is strongly counter-cyclical both in our model and in the data. Could labor adjustment costs be responsible for this counter-cyclicality? If true, then other high adjustment cost industries should see a similar counter-cyclicality. Since human capital is likely to be associated with higher adjustment costs, we check this for other high human capital industries and do not find the same pattern. In Appendix table B.18, we compute the correlation of GDP

[58] For example, the volatility of FI wage growth relative to the volatility of FI value added is 0.43, compared to 0.64 for the aggregate economy.

with an industry's employment share of total employment for high human capital industries. Like finance, healthcare is also very counter-cyclical, though this is likely due to health care demand being largely acyclical. However, we do not find strong counter-cyclicality for most other high human capital industries. In the longer 1952-2019 sample, where industry definitions are very broad, the correlation of growth rates of aggregate GDP and employment share for Finance is -0.668, compared to 0.171 for Information and -0.156 for Personal Services. In the shorter 1990-2019 sample, where finer industry definitions are available, for the nine industries likely to be high human capital,[59] the average correlation is -0.038, compared to -0.297 for finance; the only one of the nine with a more negative correlation than Finance being Legal Services.

Second, we extend our model to study labor adjustment costs. In order to model labor adjustment costs, we would need to add a state variable which records past bank labor. To avoid this, we solve a model where we shut down FLN shocks, and where bank labor is fixed at its average level. This can be interpreted as a case with infinite labor adjustment costs; we conjecture that a model with finite adjustment costs will behave like an average between this model and our baseline model.

Appendix figure B.7 shows impulse responses to a TFP shock. The responses of most variables are similar to the baseline model's impulse responses to a TFP shock shown in Figure 2.2 and discussed in section 2.3.5. However, bank employment as a share of total employment is now constant – in the data, it is counter-cyclical. Since bank equity is linear in bank labor when there is no FLN shock, bank equity is also constant, as is total corporate lending. These are all counter-factual.

Stepping outside of the model, if aggregate labor was flexible and banks had higher labor adjustment costs, then indeed even without shocks to ν_b, financial sector employment share as a fraction of total employment would be counter-cyclical, as in the data. However, without shocks to ν_b, any attempt to make financial sector employment share as a fraction of total employment more counter-cyclical will make lending less pro-cyclical, which would be counterfactual. This is because the bank's production function in the model is such that lending is proportional to financial employment.

Finally, consider stepping further outside of our model to a more general production function where lending is not necessarily proportional to bank labor. However, as long as bank employees are doing some-

[59]These are Computer and Electronic Manufacturing, Computing Infrastructure and Data Processing, Telecommunication, Professional and Scientific Services, Legal Services, Accounting Services, Architectural and Engineering, Computer System Design, and Management and Technical Consulting.

thing useful, if financial sector employment share as a fraction of total employment is higher in bad times (without shocks to ν_b affecting their productivity), banks would become especially good at intermediating capital in bad times, which is not likely to be the case in reality.

Credit shocks

Much of the FI literature has focused on credit shocks as important for lending and the business cycle. Here, we show that while they may be important, they are independent of FLN shocks and cannot produce the same patterns in the data. To capture credit shocks, we extend our baseline model by allowing the bank's maximum deposit to equity ratio κ to be time varying. Specifically, we shut down FLN shocks, setting ν_b to be its mean. We then allow κ to follow the same random process as $\nu_{b,t}$ in the baseline model, with $\kappa = 1.0$ in the bad state, $\kappa = 4.0$ in the medium state, and $\kappa = 7.0$ in the good state. The medium state κ is equal to its constant value in the baseline model, implying 80% deposits in the bank's capital structure; the bad state κ implies a credit tightening to 50% deposits in the bank's capital structure.

Appendix figure B.6 shows the impulse response to a negative credit shock, which causes κ to fall from 4.0 to 1.0. Similar to an FLN shock, output, investment, the price of capital, and lending all fall;[60] the credit spread rises, equity returns fall on impact but the expected equity premium rises. However, FLS falls implying that credit shocks cannot explain why high FLS is associated with bad times. Furthermore, financial sector employment share as a fraction of total employment falls in bad times, which is inconsistent with the data. The reason FLS and financial sector employment share fall is that a credit shock takes away deposits – a cheap source of financing – forcing banks to rely on equity. Banks shrink their balance sheets and contract lending. However, since their labor needs per dollar intermediated are unchanged, they cut their labor force significantly leading to a fall rather than rise in FLS.

[60] In this model, the quantitative effects of a credit shock on real output and investment are small. The reason for this is that models which focus on credit shocks add various frictions, making it difficult for the bank to switch from debt to equity financing when the credit constraint tightens. This difficulty creates a financial contraction which spills into the real sector. Since credit shocks are not the focus of our model, we chose to not explicitly include such frictions. As a result, it is relatively easy for banks to raise less deposits and more equity when the constraint tightens, which quantitatively weakens the real effect. Furthermore, since banks shed labor after a credit shock and since aggregate labor is fixed, the real sector sees a labor inflow and output slightly rises on impact, although it falls in the long term.

2.4 Conclusion

We study the impact of shocks to the labor needs of the financial sector on asset prices and real quantities. Theoretically, we show that the labor share of financial intermediaries proxies for higher labor needs and therefore stress for financial intermediaries. This stress is important for explaining variations in the real sector's borrowing, investment, output, and asset prices. This differs from most existing studies, which focus on the financial leverage as a proxy for stress in the financial sector.

Empirically we show that financial sector labor share positively predicts aggregate stock market returns, and negatively predicts corporate debt growth, aggregate investment growth, and aggregate output growth. At the bank-level, banks with higher labor share lend less and are associated with higher credit risk. At the firm-level, firms connected to banks with a high labor share borrow less, pay more to borrow, have higher expected default risk, and lower earnings growth. These firms do not invest significantly less on average, but do invest less if they are financially constrained.

Table 2.1. Summary statistics

This table reports the summary statistics of key variables. Key variables include financial sector labor share (FLS), growth rate of net value added (ΔNVA_Fin), and leverage ratio of financial intermediaries constructed as in HKM and AEM. It also includes aggregate GDP growth (ΔGDP), debt growth of non-financial corporate sector (ΔDebt_NCOR), investment growth (ΔINV), aggregate wage growth (ΔWage), consumption growth (ΔCons), and aggregate labor share (Agg_LS). The sample consists of annual observations from 1961 to 2019. All the variables are real.

x	Mean	StDev	AC	Corr(FLS,x)
Panel A: Financial Sector				
FLS	0.64	0.05	0.54	1.00
ΔNVA_Fin	0.04	0.07	-0.13	-0.57
HKM	18.15	6.09	0.83	0.16
AEM	17.95	11.30	0.78	0.43
Panel B: Aggregate economy				
ΔGDP	0.03	0.02	0.37	-0.30
ΔDebt	0.03	0.07	0.47	-0.27
ΔINV	0.03	0.13	0.38	-0.33
ΔWage	0.03	0.02	0.48	-0.26
ΔCon	0.01	0.01	0.48	-0.16
LS_Agg	0.55	0.01	0.92	-0.02

Table 2.2. Aggregate FLS and excess equity return

This table reports the results of aggregate-level regressions of stock market excess return at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.59	-0.59	-0.62	-0.50	-0.61	-0.98	-0.60	0.04	-0.59	-0.29
t	-1.17	-1.12	-1.15	-1.02	-1.16	-2.21	-1.20	0.09	-1.08	-0.76
Control		-2.04	-0.19	1.98	0.01	0.05	0.00	0.85	0.00	0.00
t		-1.41	-0.29	1.95	0.22	2.43	0.22	2.58	-0.01	-2.40
R2	0.02	0.01	0.00	0.03	0.00	0.10	0.00	0.08	0.00	0.03
Panel B: 1-year ahead										
FLS	0.36	0.36	0.20	0.26	0.28	0.17	0.42	0.67	0.18	0.49
t	1.96	1.90	0.85	1.60	1.39	1.00	2.78	1.83	1.13	1.86
Control		-1.32	-1.21	-2.18	5.70	2.75	-0.23	0.42	0.45	-0.11
t		-0.59	-1.15	-1.80	1.41	2.01	-3.87	1.57	2.71	-0.83
R2	-0.01	-0.02	0.00	0.01	-0.01	0.00	0.03	0.00	0.03	-0.02
Panel C: 3-years ahead										
FLS	1.93	1.98	1.70	1.67	1.90	1.35	1.99	2.59	1.61	2.56
t	2.94	2.91	2.45	2.94	2.61	2.07	3.14	3.71	2.37	3.80
Control		-5.51	-1.66	-5.70	2.97	8.30	-0.39	0.84	0.84	-0.56
t		-0.87	-1.19	-2.25	0.42	1.85	-1.67	3.08	2.35	-1.78
R2	0.09	0.10	0.09	0.15	0.08	0.15	0.11	0.10	0.13	0.11
Panel D: 5-years ahead										
FLS	5.17	5.42	4.61	4.60	4.83	4.26	5.35	6.58	4.20	5.80
t	3.25	3.42	2.70	3.54	2.66	3.22	3.83	4.28	2.86	3.83
Control		-13.25	-3.80	-12.63	28.59	12.11	-0.90	1.76	2.35	-0.59
t		-1.72	-1.61	-4.18	2.66	2.00	-3.51	2.07	3.74	-1.17
R2	0.26	0.30	0.27	0.38	0.30	0.30	0.33	0.28	0.40	0.26

Table 2.3. Aggregate FLS and debt growth

This table reports the results of aggregate-level regressions of debt growth in the non-financial corporate sector at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Debt growth at $t+k$ is defined as $\frac{Debt_{t+k}}{Debt_t}$ when $k>0$ and $\frac{Debt_t}{Debt_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.37	-0.37	-0.13	-0.30	-0.27	-0.16	-0.36	-0.54	-0.26	-0.32
t	-2.83	-2.90	-0.79	-2.44	-1.22	-1.20	-2.70	-2.61	-1.68	-2.20
Control		1.03	1.82	1.56	-0.07	-0.03	0.00	-0.24	0.00	0.00
t		1.80	5.63	7.15	-1.84	-1.92	-0.54	-0.93	-3.24	-0.68
R2	0.06	0.06	0.35	0.14	0.18	0.20	0.04	0.07	0.15	0.04
Panel B: 1-year ahead										
FLS	-0.69	-0.69	-0.50	-0.60	-0.64	-0.74	-0.69	-0.65	-0.58	-0.60
t	-5.22	-4.97	-6.16	-5.85	-7.66	-10.97	-5.49	-2.29	-6.55	-4.71
Control		-0.70	1.44	2.01	-3.79	0.67	0.01	0.05	-0.29	-0.08
t		-0.86	4.05	3.08	-1.09	0.51	0.17	0.19	-4.62	-1.59
R2	0.24	0.23	0.42	0.39	0.27	0.23	0.23	0.23	0.34	0.24
Panel C: 3-years ahead										
FLS	-1.56	-1.55	-1.38	-1.44	-1.55	-1.84	-1.53	-1.52	-1.35	-1.16
t	-5.88	-5.66	-5.89	-6.78	-6.26	-7.70	-5.38	-3.55	-5.64	-2.81
Control		-1.18	127.76	258.18	-0.33	4.10	-0.17	3.99	-0.52	-0.35
t		-0.34	1.39	1.86	-0.04	2.47	-1.52	0.13	-2.51	-1.90
R2	0.23	0.22	0.24	0.27	0.21	0.27	0.24	0.21	0.28	0.27
Panel D: 5-years ahead										
FLS	-1.99	-2.03	-1.89	-1.91	-1.98	-2.28	-1.92	-2.27	-1.70	-1.19
t	-3.87	-3.65	-3.41	-4.11	-3.74	-4.91	-3.97	-3.49	-2.84	-1.27
Control		2.04	0.64	1.64	-0.76	3.87	-0.32	-0.35	-0.69	-0.75
t		0.36	0.41	0.62	-0.06	1.26	-2.34	-1.10	-1.26	-1.99
R2	0.19	0.18	0.18	0.19	0.17	0.20	0.23	0.18	0.24	0.30

Table 2.4. Aggregate FLS and Baa - Fed Funds spread

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the finacnial labor share at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	0.11	0.11	0.11	0.13	0.10	-0.01	0.10	0.17	0.10	0.09
t	3.72	3.34	2.57	4.31	2.39	-0.40	3.74	3.24	3.47	4.14
Control		-0.47	0.24	0.30	1.28	1.73	0.02	7.26	-0.04	0.03
t		-1.94	0.01	1.23	1.65	14.23	2.18	1.72	-0.77	1.45
R2	0.09	0.13	0.07	0.13	0.15	0.90	0.13	0.12	0.06	0.08
Panel B: 1-year ahead										
FLS	0.14	0.14	0.10	0.14	0.12	0.07	0.13	0.14	0.12	0.10
t	4.21	4.24	2.90	4.50	4.35	2.01	4.88	2.85	3.28	4.32
Control		-0.04	-30.29	-5.55	1.76	0.97	0.03	-0.27	0.00	0.04
t		-0.19	-1.70	-0.24	3.42	8.94	3.15	-0.07	-0.11	4.03
R2	0.14	0.13	0.26	0.13	0.26	0.39	0.19	0.13	0.10	0.17
Panel C: 3-years ahead										
FLS	0.09	0.09	0.06	0.08	0.08	0.12	0.09	0.09	0.08	0.03
t	2.42	2.25	1.46	2.13	2.36	2.89	3.60	1.54	1.81	0.49
Control		0.24	-23.15	-21.30	0.85	-0.32	0.05	-0.30	-0.01	0.05
t		0.83	-3.29	-1.68	1.88	-1.25	2.97	-0.08	-0.13	1.93
R2	0.05	0.05	0.11	0.06	0.06	0.06	0.18	0.03	0.01	0.07
Panel D: 5-years ahead										
FLS	0.07	0.07	0.06	0.07	0.06	0.06	0.06	0.09	0.03	-0.01
t	1.78	1.70	2.02	2.28	1.96	2.02	2.23	2.19	1.04	-0.24
Control		-0.07	-5.12	6.17	0.49	0.08	0.03	3.67	-0.05	0.06
t		-0.14	-0.59	0.28	0.79	0.29	2.74	2.25	-1.69	1.81
R2	0.01	0.00	0.00	0.00	0.01	0.00	0.09	0.01	0.00	0.04

Table 2.5. Aggregate FLS and GDP growth

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. GDP growth at $t+k$ is defined as $\frac{GDP_{t+k}}{GDP_t}$ when $k>0$ and $\frac{GDP_t}{GDP_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.13	-0.13		-0.09	-0.09	-0.14	-0.13	-0.07	-0.08	-0.09
t	-4.62	-4.11		-3.60	-3.31	-5.05	-5.33	-0.93	-3.36	-3.75
Control		-0.41		0.91	-0.03	0.00	0.00	0.08	0.00	0.00
t		-1.56		6.55	-4.39	0.39	0.68	0.87	-7.95	-1.23
R2	0.07	0.09		0.40	0.29	0.07	0.06	0.10	0.30	0.08
Panel B: 1-year ahead										
FLS	-0.11	-0.11	-0.06	-0.07	-0.10	-0.17	-0.11	-0.02	-0.07	-0.06
t	-2.23	-2.06	-1.70	-2.12	-2.66	-4.87	-2.30	-0.26	-2.13	-1.61
Control		-0.30	0.32	0.79	-0.42	0.98	-0.01	0.12	-0.10	-0.04
t		-2.66	5.39	3.93	-0.54	1.83	-0.43	2.12	-4.57	-1.85
R2	0.04	0.04	0.13	0.29	0.03	0.20	0.03	0.11	0.15	0.06
Panel C: 3-years ahead										
FLS	-0.19	-0.19	-0.17	-0.14	-0.19	-0.26	-0.18	-0.17	-0.10	-0.02
t	-1.78	-1.76	-2.29	-1.95	-2.24	-3.31	-1.61	-1.08	-1.61	-0.17
Control		0.05	0.14	1.02	0.01	1.02	-0.05	0.03	-0.23	-0.15
t		0.09	0.44	1.98	0.01	1.53	-1.20	0.33	-2.80	-1.96
R2	0.02	0.00	0.01	0.09	0.00	0.04	0.03	0.00	0.15	0.10
Panel D: 5-years ahead										
FLS	-0.24	-0.27	-0.22	-0.20	-0.23	-0.25	-0.23	-0.25	-0.11	0.02
t	-1.52	-1.69	-1.98	-1.71	-1.72	-1.63	-1.44	-1.13	-0.95	0.12
Control		1.49	0.15	1.00	-1.44	0.10	-0.08	-0.01	-0.32	-0.25
t		1.38	0.31	0.31	-0.36	0.19	-1.29	-0.09	-2.02	-2.13
R2	0.02	0.04	0.00	0.05	0.01	0.00	0.04	0.00	0.17	0.16

Table 2.6. Aggregate FLS and Investment growth

This table reports the results of aggregate-level regressions of investment growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Investment growth at $t+k$ is defined as $\frac{INV_{t+k}}{INV_t}$ when $k > 0$ and $\frac{INV_t}{INV_{t-1}}$ when $k = 0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.40	-0.40	-0.13	-0.34	-0.30	-0.43	-0.42	-0.31	-0.34	-0.43
t	-7.35	-8.78	-1.87	-4.24	-2.65	-4.49	-6.50	-1.73	-3.57	-5.91
Control		-1.11	2.12	1.37	-0.08	0.00	0.04	0.12	0.00	0.00
t		-1.60	10.30	3.69	-5.25	0.35	1.48	0.48	-4.28	0.25
R2	0.11	0.12	0.70	0.21	0.35	0.10	0.11	0.11	0.18	0.09
Panel B: 1-year ahead										
FLS	-0.40	-0.39	-0.29	-0.33	-0.37	-0.63	-0.40	-0.15	-0.36	-0.34
t	-2.64	-2.41	-2.10	-2.23	-2.86	-5.48	-2.70	-0.88	-2.62	-4.19
Control		-1.71	0.83	1.61	-1.81	3.40	0.00	0.32	-0.21	-0.11
t		-4.85	5.23	3.63	-1.14	3.86	-0.06	2.13	-1.77	-1.05
R2	0.11	0.16	0.18	0.24	0.10	0.39	0.09	0.18	0.13	0.12
Panel C: 3-years ahead										
FLS	-0.43	-0.41	-0.51	-0.39	-0.45	-0.84	-0.41	-0.16	-0.33	-0.10
t	-1.89	-1.62	-2.06	-1.75	-1.78	-4.93	-1.83	-0.54	-1.28	-0.32
Control		-2.46	-0.55	0.92	2.07	5.94	-0.14	0.34	0.02	-0.33
t		-1.30	-1.11	0.81	0.43	4.67	-1.28	1.73	0.06	-1.14
R2	0.01	0.02	0.00	0.00	0.00	0.18	0.02	0.01	-0.03	0.02
Panel D: 5-years ahead										
FLS	-0.06	-0.07	-0.20	-0.06	-0.03	-0.28	-0.02	0.23	0.15	0.69
t	-0.17	-0.17	-0.55	-0.19	-0.09	-0.78	-0.07	0.51	0.35	1.28
Control		0.18	-0.92	0.00	-2.62	2.92	-0.20	0.37	0.27	-0.37
t		0.05	-1.37	0.00	-0.42	1.32	-1.26	1.44	0.55	-0.82
R2	-0.02	-0.04	-0.02	-0.04	-0.03	0.00	0.00	-0.02	-0.03	0.03

Table 2.7. Bank level FLS and bank loan growth

This table reports the results of predicting loan growth in the U.S at $t+k$ by bank holding companies' labor share (FLS) at t using panel bank holding company data from FR Y-9C. This table presents both the univariate and multivariate regression results with bank holding company and year or state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$\Delta Loan_{i,t+k} = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}$$

where $\Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t:t+k}) + Avg(Loan_{i,t-k+1:t})}$ is the loan growth of bank i over a 3-year window ($k = 3$). Column (1) to (4) present the predictability results with dependent variable to be growth rate of total loan and column (5) to (8) present the predictability results with dependent variable to be growth rate of commercial and industrial (C&I) loan. The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The online appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total loan growth				Commercial&Industrial loan growth			
FLS	-0.17***	-0.14***	-0.16***	-0.14***	-0.18***	-0.15***	-0.15***	-0.14***
	(-26.17)	(-22.19)	(-14.19)	(-13.35)	(-17.14)	(-14.66)	(-8.43)	(-7.76)
BHC Size			-0.08***	-0.08***			-0.08***	-0.07***
			(-9.08)	(-9.21)			(-5.86)	(-5.36)
BHC ROA			0.78	-0.20			0.42	-0.51
			(1.08)	(-0.27)			(0.37)	(-0.44)
BHC Capital Ratio			-0.26*	-0.10			0.28	0.54**
			(-1.84)	(-0.71)			(1.21)	(2.31)
BHC NPL Share			-4.44***	-3.62***			-10.45***	-9.24***
			(-12.33)	(-9.99)			(-17.00)	(-14.99)
BHC Interest Expense			-4.71***	-3.94***			-3.06***	-2.33***
			(-9.69)	(-8.35)			(-4.46)	(-3.38)
BHC ΔEBIT			0.01***	0.01***			0.01***	0.01***
			(9.06)	(8.25)			(6.47)	(5.65)
N	36969	36857	32555	32430	36949	36837	32516	32391
adj. R^2	0.501	0.546	0.542	0.577	0.401	0.428	0.436	0.459
BHC FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FEs	No	Yes	No	Yes	No	Yes	No	Yes

Table 2.8. Bank level FLS and bank credit risk

This table reports the results of predicting of bank holding company's average expected default frequency (EDF) from $t+1$ to $t+3$ by bank holding companies' labor share (FLS) at t using panel bank data from FR Y-9C. This panel presents both the univariate and multivariate regression results with bank holding company and state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$Avg(EDF_{i,t+1:t+k}) = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}.$$

The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The online appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1992 to 2011.

	(1)	(2)	(3)	(4)
	Expected default frequency (EDF)			
FLS	1.47***	1.32***	1.61***	1.44***
	(7.83)	(6.90)	(5.77)	(5.17)
BHC Size			0.52***	0.34***
			(4.35)	(2.72)
BHC ROA			15.84	13.77
			(1.26)	(1.01)
BHC Capital ratio			-9.78***	-8.84***
			(-3.74)	(-3.41)
BHC NPL Share			-3.10	-3.33
			(-0.39)	(-0.37)
BHC Interest Expense			7.84*	6.81
			(1.76)	(1.35)
BHC ΔEBIT			-0.05**	-0.05**
			(-2.33)	(-2.31)
N	6080	5928	5863	5706
adj. R^2	0.589	0.654	0.601	0.662
BHC FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State_Year FE	No	Yes	No	Yes

Table 2.9. Bank level FLS and firm credit

This table reports the results of predicting borrowing quantity, price of bank loans, or distance to default for non-financial U.S firms over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \Delta Loan\ Amount_{i,j,t+k} = 2\frac{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} - \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} + \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}$ is the growth rate of loan borrowing in Panel A, $y_{i,j,t+k} = Avg(Loan\ Spread_{i,j,t+1:t+k})$ the average loan spreads measured as"All-in-drawn" from Dealscan Loan Pricing in Panel B, and $y_{i,j,t+k} = Avg(D2D_{t+1:t+k})$ is default risk in Panel C ($k = 3$). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio, interest expense and earning growth) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return and credit rating). The regressions are estimated under different fixed effect specifications. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks and firms. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)
	Panel A: Loan borrowing growth		
FLS	-0.49***	-0.46**	-0.51**
	(-2.83)	(-2.26)	(-2.92)
N	15277	14916	15262
adj. R^2	0.121	0.123	0.123
	Panel B: Credit spread		
FLS	0.36*	0.29*	0.33*
	(1.88)	(1.70)	(1.87)
N	15008	14659	15000
adj. R^2	0.461	0.469	0.470
	Panel C: Distance to default		
FLS	-1.84***	-1.66***	-1.61***
	(-3.75)	(-2.79)	(-3.14)
N	14353	13994	14337
adj. R^2	0.499	0.507	0.514
BHC FEs	Yes	Yes	Yes
Year FEs	Yes	No	No
Firm State_Year FEs	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes

Table 2.10. Bank level FLS and firm real outcomes

This table reports the results of predicting non-financial U.S firms' changes in investment rate or earnings growth over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$ for investment rate changes in Panel A and $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ for earnings growth in Panel B ($k = 3$). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio and interest expense) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return, tangibility and credit rating). The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks and firm. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)
	Panel A: Investment rate change		
FLS	-0.03	-0.04	-0.04
	(-0.80)	(-0.96)	(-1.09)
N	14701	14337	14684
adj. R^2	0.267	0.270	0.285
	Panel B: Earnings growth		
FLS	-0.68**	-0.73**	-0.64**
	(-2.07)	(-2.42)	(-2.06)
N	14799	14427	14782
adj. R^2	0.005	0.004	0.008
Bank FEs	Yes	Yes	Yes
Year FEs	Yes	No	No
State_Year FEs	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes

Table 2.11. Calibration

This table presents the values of the parameters used to solve the model.

Variable	Parameter	Description
Standard parameters		
β	0.98	Time discount factor
ρ	2.0	Risk aversion
α	0.35	Capital share in production
δ	0.064	Depreciation rate
g	0.018	Growth rate
$\nu_{k,0}$	2.5	Strength of capital adjustment cost
$\nu_{k,1}$	$1+g$	Target (zero cost) capital growth
Z_t	(0.95,1.00,1.05)	TFP
Non-standard parameters		
$\nu_{b,t}$	(0.0223,0.0180,0.0137)	FI labor to assets ratio
κ	4.0	FI leverage ratio
λ_0	0.025	Liquidity preference strength
λ_1	0.50	Liquidity preference curvature
υ_0	0.35	Equity issuance cost strength
υ_1	8.0	Equity issuance cost curvature
$\nu_{cd,0}$	0.05	Deviation from target debt cost strength
$\nu_{cd,1}$	0.50	Target (zero cost) debt to capital ratio

Table 2.12. Model moments

In Panel A, the data moments are from BEA tables 1.1.3 and 1.1.5 for 1949-2018. We define consumption as Personal Consumption Expenditures and Investment as Fixed Investment; we define private output as Gross Domestic Output minus Government expenditures. To compute each variable as a share of private output, we use nominal quantities; to compute volatility and correlation with private output, we use real quantities. In Panel B, the deposit rate is from Figure 1 in (Drechsler et al., 2017b), which is available for 1997-2013. The corporate bond return is for ICE BofA BBB total return index. In Panel C, we present the slope from regressing financial employment (USFIRE) as a share of total employment (PAYEMS) on GDP. Since both variables are non-stationary, we run regressions either on HP-filtered quantities, or on growth rates. For the data moments, t-statistics are shown in parentheses.

Panel A: Business cycle moments

	Data			Model		
x	$E[\frac{x}{y}]$	$\frac{\sigma[\Delta x]}{\sigma[\Delta y]}$	corr(Δx,Δy)	$E[\frac{x}{y}]$	$\frac{\sigma[\Delta x]}{\sigma[\Delta y]}$	corr(Δx,Δy)
c	0.79	0.61	0.81	0.80	0.62	0.99
inv	0.21	2.28	0.88	0.20	2.38	0.98

Panel B: Financial moments

	Data		Model	
x	$E[x]$	$\sigma[x]$	$E[x]$	$\sigma[x]$
r^{dep}	2.6	1.5	4.7	2.0
$r^{cd} - r^{dep}$	5.9	7.1	2.2	0.3
$r^{e} - r^{dep}$	7.2	17.5	2.4	6.6

Panel C: Relationship between N_b/N and GDP

	HP-filtered		Growth	
Data 1951-2021	-0.45	(-11.41)	-0.29	(-6.60)
Data 1951-2019	-0.56	(-8.43)	-0.54	(-3.74)
Model	-0.58		-0.17	

Table 2.13. Response to TFP and FLN shocks

The first column of this table reports the correlation between model implied and actual quantities of interest for 1948-2020. The model is simulated with a time series of TFP and FLN shocks extracted from the data. The extraction procedure is described in the text. The second column of this table is similar, but the simulation includes TFP shocks only, with FLN shocks set to their average level. The quantities of interest are GDP growth, investment growth, debt growth, the Baa - Fed Funds spread, and financial sector employment share as a fraction of total employment.

	TFP & FLN	TFP only
ΔGDP	0.45	0.44
ΔINV	0.49	0.46
ΔDEBT	0.33	0.17
Baa-FF	0.15	-0.11
$\frac{N_b}{N}$	0.51	-0.08

Figure 2.1. Impulse responses to an FLN shock

This figure plots the impulse response functions to a one standard deviation FLN shock, $v_{b,t}$. To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the FLN shock at their average values. At $t = 1$, the TFP shock remains at its average value, but FLN rises unexpectedly. After $t = 1$, the TFP shock remains at its average value, while the FLN shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a high $v_{b,t}$, while $t > 1$ values are expected values.

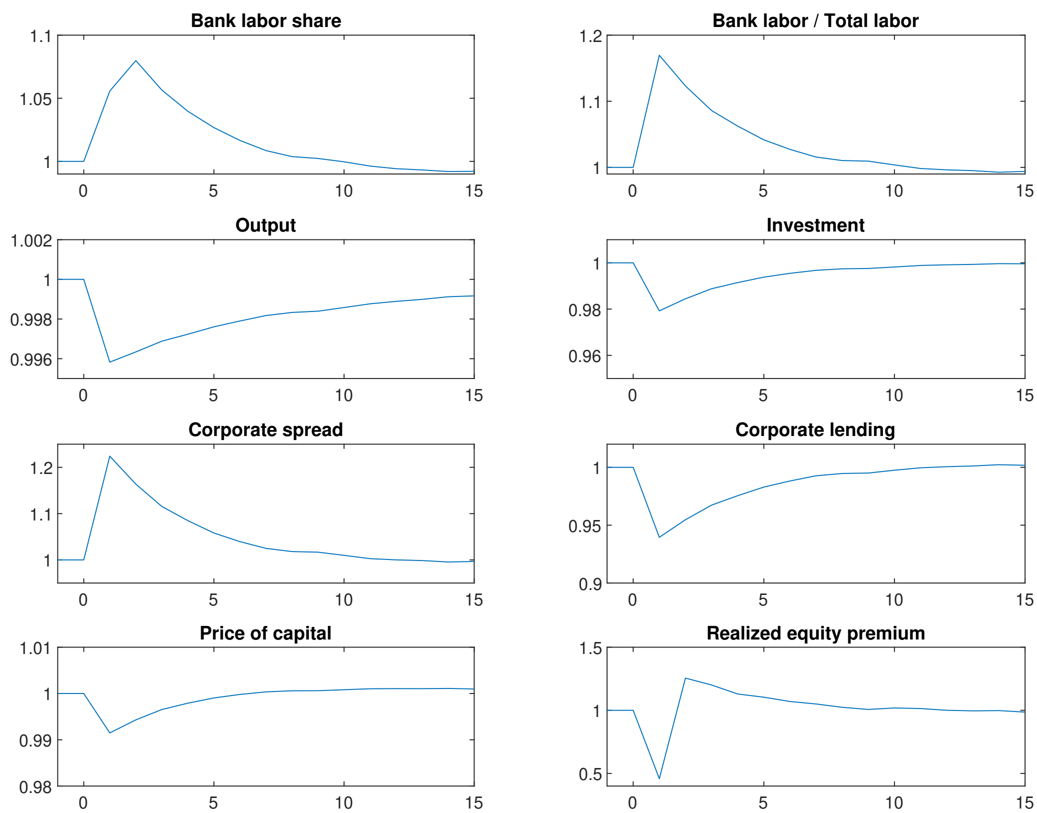


Figure 2.2. Impulse responses to TFP shock

This figure plots the impulse response functions to a one standard deviation shock to TFP. To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the FLN shock at their average values. At $t = 1$, the FLN shock remains at its average value, but TFP falls unexpectedly. After $t = 1$, the FLN shock remains at its average value, while the TFP shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a low TFP, while $t > 1$ values are expected values.

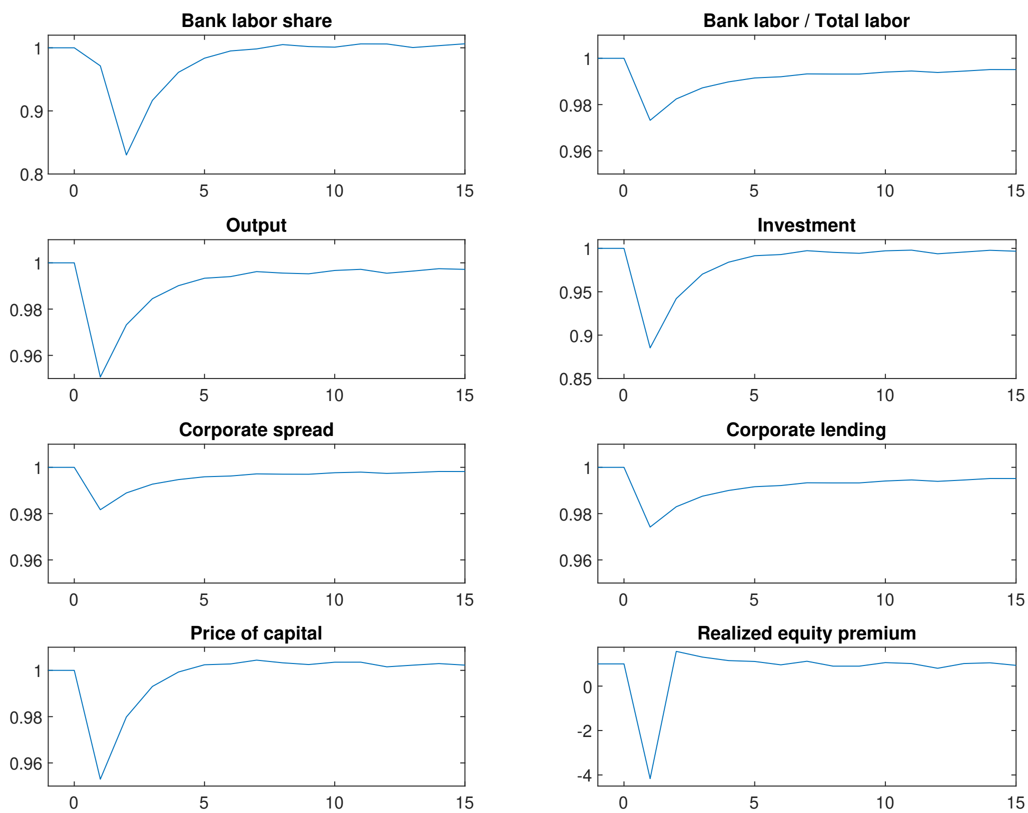
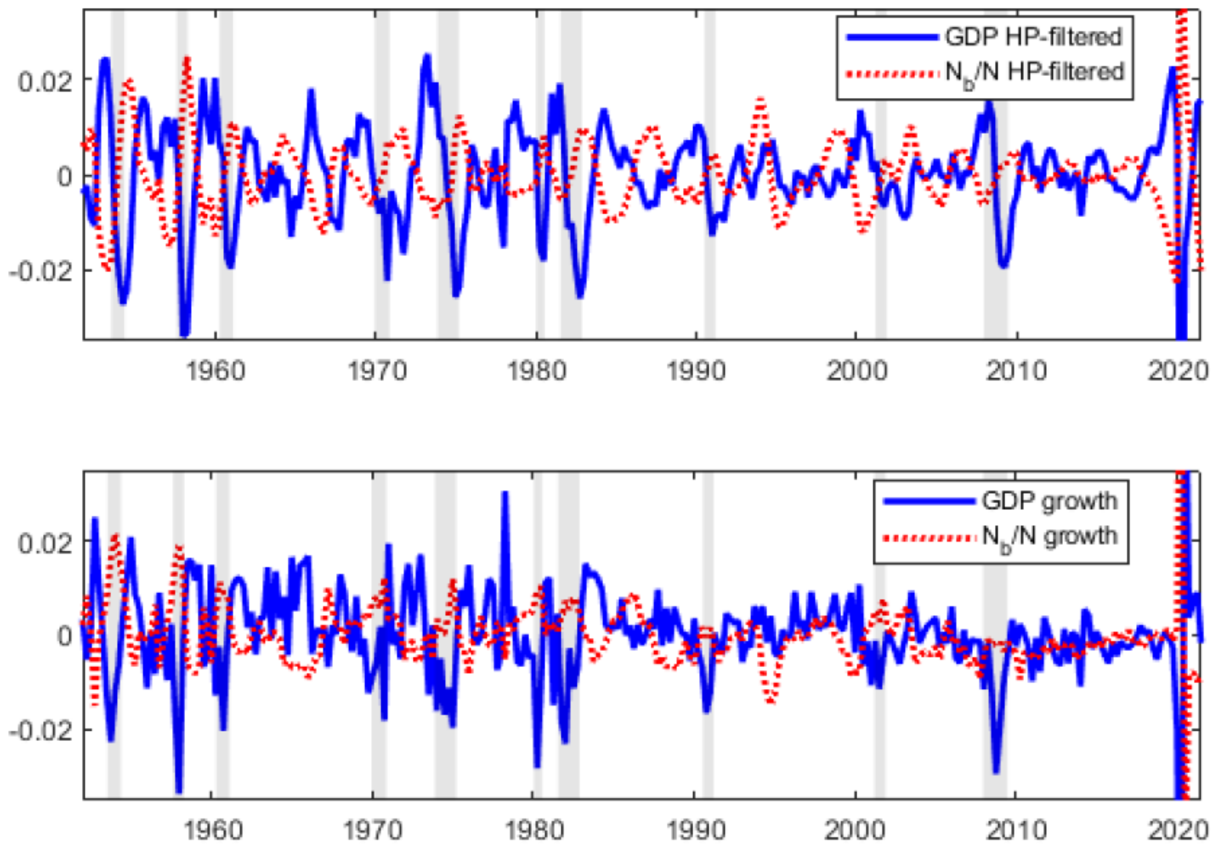


Figure 2.3. Financial sector employment share of total employment, time series

This figure plots the financial sector employment share of total employment over time, and compares it to GDP. The series are USFIRE, PAYEMS, and GDPC1 respectively in FRED. Since both series are non-stationary, the top panel plots HP-filtered values and the bottom growth rates.



Chapter 3

Appropriated Growth

3.1 Introduction

Intangible capital continues to play an ever-larger role in the operation of the modern firm and economic growth.[1] Despite its importance, however, how to best split its reward among a firm's owners and employees remains debated. An established view argues that, because investment in intangible capital generates knowledge spillovers which preclude owners from fully capturing the reward, it will be underprovided (Arrow (1962)). To shield owners' investment by preventing such spillovers, then, is to maximize intangible investment and therefore growth. A widespread mechanism by which firms attempt to achieve this is through non-compete agreements that restrict employees from moving to competing firms and taking knowledge capital with them.

This view, however, ignores the effect on workers' behavior, especially those whose effort is crucial to the creation of knowledge and new intangible assets. If this investment creates know-how that becomes inalienable to these key employees, then the ability of workers to take this knowledge with them to another firm will enhance their prospects and worth—their outside option value. Restricting worker mobility may thus *reduce* their motive to exert effort and thus diminish the ability of the firm to grow its intangible capital. Therefore, an important channel overlooked by the established view is the effect that agents' mobility has

[1] We entertain a broad notion of intangible capital that encompasses the capital built from knowledge, such as information technology (IT), research and development (R&D) processes, and human and brand capital. Corrado et al. (2009) stress the importance of accounting for intangible capital when measuring economic growth.

on their incentives.

In this paper, we investigate the relationship between intangible investment and worker mobility both theoretically and empirically. In doing so, we also address a policy-relevant question: what degree of mobility restrictions maximizes investment in intangible capital? An answer to this question could not be more timely, as the Federal Trade Commission (FTC) recently put forward an expansive proposal to prohibit companies from limiting workers' ability to work for rivals.[2]

We proceed in three steps. First, we build a novel structural model to understand the mechanisms behind the dynamic connection between intangible investment and worker incentives. Second, we present empirical evidence that supports the key theoretical predictions and that serves to discipline the model's calibration. Third and finally, we use our calibrated model to evaluate how different counterfactual enforcement policies would impact intangible investment. We find that the current set of policies to be near growth-optimal, as we describe below.

In our first step in Section 3.2, we lay out the elements of our structural dynamic agency model. It features a distribution of heterogenous firms making decisions on intangible capital accumulation and agent's compensation in the presence of knowledge spillovers. Firms are owned by deep-pocketed investors and invest in intangible capital to maximize profits. Investment, however, requires a specialist (the agent) to exert effort to capitalize the investment into the firm's productive technology. The agency problem arises as the specialist can alternatively shirk and receive private benefits.

A novelty of our model is the interaction between the specialist's incentives and the knowledge accumulation that accompanies intangible investment. As the firm invests, the specialist *appropriates* a portion it in the sense that it adds to their inalienable skill (knowledge), which they can take with them if they join another firm. Appropriation therefore improves the value of the specialist's outside option, akin to a knowledge spillover. Thus, investment enhances profits, but it also raises the probability that the specialist may leave the firm, an event which is costly to investors (Israelsen and Yonker (2017) provide empirical evidence of the firm value loss from specialist departures). This tension locates the heart of our model.

We characterize the model's solution in Section 3.3. To solve the dynamic agency problem, the firm's owners write contracts that prescribe policies of intangible investment, termination, and compensation. In

[2] https://www.nytimes.com/2023/01/05/business/economy/ftc-noncompete.html

particular, the contract uses deferred and current compensation based on the specialist's skill (i) to induce effort by the specialists and (ii) to retain them. First and common to other dynamic agency models of investment, for example DeMarzo et al. (2012), sequences of intangible capital growth are associated with greater levels of deferred compensation. Promising higher levels of future compensation is required to sustain the specialist's effort. Larger promises mitigate the agency conflict and bolster the expected return on intangible investment. Consistent with this prediction, Eisfeldt et al. (2022) document empirically the positive association between intangible capital and deferred compensation.

At the same time, a second effect is present in which investment raises the specialist's outside option through the knowledge spillover. In contrast to the prediction above, investment can potentially aggravate the agency conflict as it becomes more costly to induce effort, lowering the expected return on intangible investment. In consequence, and new to the dynamic contracting literature, we show that it is optimal to sometimes pay bonus-like payments to retain skilled employees, even at low values of deferred compensation if the specialists's skill and likelihood of leaving becomes high enough. This new insight, which derives from the interaction between appropriation and agency frictions, shows that the relationship between specialists' outside option values and firms' intangible investment is nuanced.

In our model, both effort and retention forces are present and our calibrated structural economy clarifies when each one dominates. Correspondingly, our model solution requires the joint determination of specialists' and investors' value functions on the specialist's outside option; that is, the specialist's ability to appropriate intangible capital affects the prescriptions of the optimal contract. Our computational work is also a contribution as it solves this interconnected problem that, mathematically, requires an edge of the state space to satisfy a set of fixed points.

In the second step of our analysis in Section 3.4, we formulate an empirical environment to test and ground these model predictions as well as to provide key parameter estimates for our model calibration. Empirically, we identify *specialists* as agents within firms that are crucial for the development of intangible capital: i) chief executives or ii) employees who work in high-skilled industries. Informed by labor market search theory, we construct a metric of the value of specialists' outside options that depends on the compensation structure and mobility across different industries and states.

We then explore how the value of specialists' outside options are impacted in response to an exogenous change in their mobility. Specifically, we use variation in states' enforcement of non-compete agreements to establish causally that stricter enforcement lowers the value of outside options, reduces employee turnover, and raises firms' investment rate in intangible capital. The empirical evidence is consistent with the predicted forces within the model, and we run a host of robustness tests to confirm the validity of our setup. More broadly, our results cast doubt on the established view that ignores the impact of mobility restrictions on agents' incentives.

In the third and final step, we calibrate and analyze our model in Section 3.5 before turning towards using it to evaluate how different counterfactual enforcement policies would impact intangible investment and value in Section 3.6. We use indirect inference to estimate the key parameters affecting the evolution of specialists' skill by targeting the identified coefficients of our empirical analysis. We then verify that the model's predictions match well what we see in the data. In particular, we exploit the dynamic nature of the model to provide unique and distinguishing predictions: one such example is that historical sequences of beneficial shocks to a firm's intangible capital raise profits, investment, and agents' stock of deferred compensation, ensuring their commitment to exert effort.

The counterfactuals center on assessing how different levels of knowledge appropriability—a factor that non-compete agreements likely influence—determine the intangible investment rate and owners' and specialists' contract values. Our analysis produces a hump-shape in both expected investment rates and values with respect to appropriability. Generally speaking, the current set of mobility restrictions is close to optimal and adequately balances the interests of owners and employees. This perhaps is not too surprising as the current set of contracts have been formed over decades through the repeated negotiations among both parties.

The hump-shape, furthermore, underscores the importance of studying model counterfactuals that jointly account for the equilibrium forces of appropriability, turnover, agency conflicts, and the return of investment rather than relying on extrapolations of local average treatment effects to inform policy. While our model necessarily abstracts from the full complexity of reality, the core idea in which both owners and agents have their own separate interest remains and points towards an interior level of appropriability. Policies that severely limit outside options, in strict adherence to Arrow's (1962) traditional view, or policies that substantially bolster outside options, by banning non-compete agreements as prescribed by Shi (2022), are likely to be sub-optimal and to lead to a reduction in value and the rate of intangible investment.

3.1.1 Literature

Work in applied theory studies the role of intangible capital and worker characteristics on firms' risk profiles, investment, and production functions.[3] Donangelo (2014b) argues how firms' limited control over their most important factor, labor, represents a risk source to owners. Belo et al. (2017) show this risk is amplified in industries that rely heavily on high-skilled labor. In this vein, Eisfeldt and Papanikolaou (2013) look at the organizational capital created by skilled labor and its implications for the cross-section of expected returns. A key systemic risk source they identify relates to the likelihood of key personnel leaving the firm. Dou et al. (2021) develop a model of customer capital, a type of intangible asset, which is influenced by the talent of worker who may leave the firm, and derive asset pricing implications.

More recently, Eisfeldt et al. (2022) structurally estimate a production function that includes high-skilled labor who earn a substantial part of their income in the form of equity-like claims and find strong complementarity with physical capital. Baslandze (2022) provides empirical evidence and estimates a structural model examining how entrepreneurship and innovation dynamics are affected by labor mobility. None of these papers model an agency conflict that is integral to understand how mobility affects agents' incentives. Nor do they seek to understand how these forces impact intangible investment and growth.

Complementary to these theories is a growing empirical literature on the determinants of labor mobility and its impact on firm outcomes. For example, Jeffers (2020) uses detailed employee-employer matched data to examine how the enforceability of non-compete agreements impacts firms' physical investment. Johnson et al. (2023) examine firm innovation output around changes in the enforcement of non-compete agreements. Babina and Howell (2022) show that increases in corporate research and development spur employee departures to join startups. Fedyk and Hodson (2022) explore the career migration of employees and find that technical skill sets of individuals negatively forecast the financial and operational performance of the firm. None of these papers, however, use an equilibrium model to study counterfactuals on worker mobility and investment through the channels we lay out.

[3] A short list is Ai et al. (2013), Sun and Xiaolan (2019), Donangelo et al. (2019b), Kogan et al. (2020), Crouzet and Eberly (Forthcoming), Crouzet et al. (2022), Jiang et al. (2022), Liu and Ma (2021), and Li (2023).

Our theoretical environment builds upon previous work on dynamic agency models.[4] In the class of models that feature limited commitment, for example Bolton et al. (2019) and Ai et al. (2021), contract separation does not occur in equilibrium, as it is optimal to readjust the contract so that both parties' participation constraints remain satisfied. That is, (almost surely) *all* separation in these models is exogenous.[5] In contrast, because our economy features moral hazard in which agents can shirk, the dynamic contracting environment prescribes separation in equilibrium. Specialists' probability of leaving the firm and exercising their outside option is thus a choice influenced by their ability to appropriate knowledge.

In contrast to much of the dynamic contracting literature, we look at the implications of agency conflicts on the growth rate of the economy. Closely related papers are Dow et al. (2005) and Albuquerque and Wang (2008), though their focuses are on asset prices and investment, not economic growth. Lustig et al. (2011) attribute the rise in the disparity across executive compensation since the 1970s to a compositional shift of productivity growth from vintage-specific to general growth, which impact the value of these executives' outside options, but they do not study how worker mobility affects economy-wide growth.

The literature on growth is expansive and seminal entries date back at least to Schumpeter (1942), Solow (1956), Arrow (1962), and more recently Romer (1990b).[6] Similar to Uzawa (1965) and Lucas (1988), we focus on the growth of an input into a firm's production function. In this sense, our notion of intangible capital is close to the spirit of Prescott and Visscher's (1980) organizational capital. As described in Crouzet et al. (Forthcoming), this capital is stored in employees, but we focus on their ability to leave the firm and its impact on investment.

Romer (1990a) distinguishes rivalry from excludability. Because intangible capital is in part knowledge, it is possible to talk about knowledge spillovers, that is, incomplete excludability. Specialists' outside options are the conduit through which intangible investment becomes partially nonexcludable. This is similar to Lucas (1988) where the production of a nonrival, nonexcludable good occurs as a side effect of production. This side effect, however, is internalized in our setup by the firm's owners. Moreover, adjustment costs

[4] A partial list is DeMarzo and Sannikov (2006), Biais et al. (2007), Sannikov (2008), He (2009), DeMarzo et al. (2012), Xiaolan (2014), Ai and Li (2015), Ai and Bhandari (2021).

[5] In Dou et al. (2021) a firm's owners experience events in which they can choose to maintain or terminate the contract with their agent, but the arrival of the event is exogenous.

[6] Many contributions constitute this literature. An incomplete list is Grossman and Helpman (1991), Aghion and Howitt (1992), Comin and Gertler (2006), Atkeson and Kehoe (2007), Acemoglu (2009), Akcigit et al. (2015), Ward (2020), and Çelik and Tian (Forthcoming).

on the investment of intangible capital creates quasi-rents that allow for intentional private investment, much like in Romer (1986). We further connect the growth in intangible capital to their creators' incentives and compensation.

Finally, our paper is close to Shi (2022) who, like us, studies the macroeconomic impact of restrictions on workers' mobility. We share her idea that mobility is an important determinant of growth, but we differ from her analysis in a few ways. Most acutely, our model features an agency conflict that is absent in her setup. As a result, we have different predictions regarding the optimal restriction on mobility. Her two main assumptions are i) bilateral efficiency, so firm value is simply split between owners and agents according to fixed Nash bargaining weights and ii) incumbent firms with non-competes fully extract the implied rent from entrants, which are assumed to be relatively more productive. Consequently, she argues for a complete ban on non-competes as they only affect entrants but not the split of firm value. In our model, the optimal contract makes firm value and investment dependent on agents' stake in the firm. High mobility reduces the investment return to the firm's owners, so a complete ban is also suboptimal. Our model instead prescribes an interior level of optimal enforcement relative to the extrema prescribed by Arrow (1962) and Shi (2022).

3.2 An Agency Model of Mobility and Intangible Investment

In this section, we develop a dynamic agency model that co-determines investment in intangible capital with the allocation of its rents. Time is continuous and infinite. Firms are heterogeneous. Investors own the firms, have deep pockets, and hire specialists to exert effort towards developing the firm's intangible capital that complements physical capital and labor in the production of a final good. Specialists, which could be skilled employees or executives, face limited liability. All economic agents are risk neutral but investors discount at rate $r > 0$ and specialists at rate $\gamma > r$ (see DeMarzo and Sannikov (2006) for details on this assumption).

3.2.1 Production Technology and Profits

The production technology uses intangible capital N, physical capital K, and (unskilled) labor L. Physical capital and labor are rented in competitive markets. At every instant the firm produces profits Π

$$\begin{aligned}\Pi_t &= \max_{K,L\geq 0}\left\{\bar{A}(N_t^{\phi}K_t^{1-\phi})^{\alpha}L_t^{1-\alpha} - RK_t - W_L L_t - g_t N_t - C(g_t N_t, N_t)\right\}\\ &= ZN_t - g_t N_t - C(g_t N_t, N_t),\end{aligned} \tag{3.1}$$

where $Z > 0$ doubles as the marginal product of intangible capital and is a function of productivity $\bar{A}$, the capital share α, intangible capital's share of total capital ϕ, the wage W_L, and the rental rate R.

The profit function features a form of "AK" technology, common to growth models (see Jones and Manuelli (2005)). The rate of accumulation of intangible capital will be a firm's primary choice that affects the economy's endogenous growth. Jorgenson (2005) attributes the lion's share of the US growth experience to the accumulation of (quality-adjusted) capital rather than technical change, especially in regards to the accumulation of information technology over the period 1995–2002.

Because investments in knowledge-intensive activities are often of long duration and require sustained expense to succeed, we place a variable adjustment cost $C(\cdot)$ on the investment rate of intangible capital g. We assume that it is homogeneous of degree one in both arguments and takes a quadratic form

$$gN + C(gN, N) = Nc(g) \equiv N\left(g + \frac{\theta}{2}(g - \delta_N - x)^2\right),$$

where θ is the adjustment cost parameter and x locates the average investment rate. The adjustment cost creates value in the form of accruable rents, captured by (intangible) marginal q, that can be allocated to the firm's investors and specialists.

3.2.2 Intangible Capital and Agency Conflict

Intangible capital comprises information technology, research and development design, business processes, and human and brand capital. It is because part of this knowledge is inalienable to employees that it differs from physical capital. Its inalienability affects their outside options and their incentive compatibility constraints on remaining with the firm. There is no such meaningful inalienability or potential appropriation with physical capital—you simply cannot take it with you.

Intangible capital is created by the hands of specialists. Its development is gradual: for example, the term research and development reflects the difficulty in creating something truly new and useful, which takes time; advertisements that build brand capital often take the form of campaigns. We posit that specialists' collective effort $e_t \in \{0, 1\}$ determines the growth of intangible capital that evolves as

$$dN_t = (g_t e_t - \delta_N) N_t dt + \sigma_N N_t dB_t. \tag{3.2}$$

Realized growth is hindered by obsolescence $\delta_N > 0$ and varies with a Brownian motion B_t with volatility $\sigma_N > 0$. Volatility here measures its inherent riskiness, which could be stochastic obsolescence driven by competitive forces, or variation in the quality of intangible capital (see Ward (2022) for perspective on this modeling assumption). Thus, σ_N summarizes the uncertainty over the quality of the firm's intangible capital and the degree to which specialists can hide their effort.

When specialists shirk ($e_t = 0$) they receive private benefits commensurate to the magnitude of intangible investment, $\lambda g_t N_t dt$, where the parameter $\lambda > 0$ measures the severity of the agency friction. Larger flows, $g_t N_t$, make it easier to waste resources. Because specialists have their own private interest and because their effort choice is not observable, investors write a contract that gives specialists the incentive to exert effort and maximize firm value.

3.2.3 The Contracting Environment

We assume that the firm's traditional inputs, K and L, and the firm's (cumulative) cash flow process $\{\Pi_t : 0 \leq s \leq t\}$ are observable and contractible. Therefore from (3.1), cash flow realizations allow investors to write contracts on intangible capital's growth. Investors thus monitor physical capital, employment, and cash flows to discover the firm's level of intangible capital N.

The contract, represented by $C = (g, U, \tau)$, specifies intangible investment g_t, specialists' cumulative current compensation U_t which must be nondecreasing by limited liability, and a termination time τ, all of which depend on the stock of intangible capital N_t. As we will show, a novelty of our model relative to

DeMarzo et al.'s (2012) is that U_t will account for the history of retention payments made to agents to keep them in the firm.

Appropriation, Specialists' Skill, and Outside Option

The contract can be terminated at any time. In this event, investors recover a fraction $0 \leq l < 1$ per unit of intangible capital and specialists receive the value of their outside option. We assume that specialists' skills are always in demand and we do not take a stand on whether the specialist leaves for an existing firm or to start a new one. Thus their outside option is to leave the current firm and join a different firm with $a_t N_t$ units of intangible capital, where $a_t > 0$ captures their appropriation of the current firm's capital that we succinctly refer to as *skill*. Because it is transferable, we view this skill as a general trait and not a firm-specific one.

We emphasize that this skill, however, is independent of their ability to add value to the current firm at which they are working and instead measures the market's assessment of the value of knowledge they could potentially bring to a new firm. For example, a head marketer discovers that a particular branding strategy or campaign tends to attract more demand; this skill could be useful to another firm. As another example, research and development that has led to a seminal insight could be useful in forming a new firm. In the language of Crouzet et al. (2022), skill measures the fraction of the current firm's capital that is stored and can be potentially be appropriated by specialists.

There are two properties of appropriation that we aim to capture. First, it should grow with the firm's investment in intangible capital. Bell et al. (2019) show that the majority of inventors are a product of their environment ("nurture") rather than possess innate ability ("nature"). The process of investment creates more knowledge that, through inalienability, leads to some value being appropriated by specialists. Second, there should be variation in specialists' skill, whether it be induced by market-driven fluctuations in the value of that skill or government policies on competition among firms and workers.

Altogether, we specify the dynamics of their skill of appropriation as

$$da_t = \kappa(g_t - \delta_N)a_t dt + \sigma_a a_t dB_{a,t}, \tag{3.3}$$

where $\kappa > 0$ is a rate of learning from investment and where specialists' skill fluctuates with an independent

Brownian motion, B_a, with volatility $\sigma_a > 0$. We also call κ the appropriation parameter. It interacts with the firm's *net* growth rate of intangible capital and, therefore, an agent's skill could depreciate. We assume the expenditure rate g_t raises specialists' outside option regardless of effort choice. While specialists' skill could potentially become very large, we will show that the incentive compatible contract bounds this process by optimally giving retention payments.

Specialists will leave their current firm when their wealth falls below what they could have in a new firm, $W_0(a_t, a_t N_t)$—the value of their outside option—which depends on their skill, how much capital the new firm will have, as well as their bargaining power. Specialists and investors bargain when the contract is initiated to determine specialists' initial wealth. If investors had all bargaining power, then $W_0 = W_0^I \equiv_{W \geq 0} P(a_0, N_0, W)$; conversely, if specialists had all power, then $W_0 = W_0^S \equiv \max\{W : P(a_0, N_0, W) \geq 0\}$. More generally, we blend the two extremes with a parameter $\psi \in (0,1)$ by setting $W_0 = \psi W_0^S + (1-\psi) W_0^I$.

To summarize termination, investors recover intangible capital worth lN_t and specialists leave. Specialists then join a new firm with $a_t N_t$ units of intangible capital, skill level a_t, and initial wealth $W_0(a_t, a_t N_t)$. Investors finance the new capital in part with the proceeds of their recovered capital. If $a_t > l$, managers have effectively used appropriation to dilute investors. Alternatively, this can be interpreted as specialists exercising their ability to leave and instead receiving a retention payment to keep them in the firm (although this would not result in separation). If $a_t \leq l$, then $l - a_t$ represents a net liquidating payout to investors.

The Contracting Problem

Given the contract, $C = (g, U, \tau)$, specialists choose their action process to maximize the present value of current compensation, their consumption of private benefits, and the value of their outside option,

$$W(C) = \max_{e_t \in \{0,1\}: 0 \leq t < \tau} \mathbb{E}^e \left[\int_0^\tau e^{-\gamma t} (dU_t + (1-e_t)\lambda g_t N_t dt) + e^{-\gamma \tau} W_0(a_\tau, a_\tau N_\tau) \right],$$

where the expectation $\mathbb{E}^e[\cdot]$ is taken under the probability measure conditional on specialists' effort process.

When the contract is written, the firm has N_0 units of intangible capital and specialists have skill a_0. Investors write a contract to maximize firm value, the present value of cash flows less current compensation paid to specialists plus recovery in contract termination,

$$P(a_0, N_0, W_0) = \max_C \mathbb{E}\left[\int_0^\tau e^{-rt}(\Pi_t dt - dU_t) + e^{-r\tau} l N_\tau\right]$$

$$\text{s.t. } C \text{ is incentive compatible and } W(C) = W_0. \tag{3.4}$$

We formulate incentive compatibility below. A novelty of our model is the co-dependence of specialists' and investors' value functions on the specialist's outside option value, $W_0(\cdot)$. As we will see, this co-dependence impacts the maximum values that could be attained by both parties and, more broadly, the implementation of the optimal contract. This, in turn, affects mobility, investment, and the overall growth rate of the economy.

Importantly, we do not impose a participation constraint on (3.4) as we allow for specialists to leave the firm. This assumption distinguishes our paper from limited commitment models of Ai et al. (2021) and Bolton et al. (2019), among others, as our model's contract will allow for endogenous separation of specialists from firms.

3.3 Model Solution

We first determine optimal investment in intangible capital without an agency problem. We then characterize the optimal contract in the presence of an agency conflict. We consider two model cases to clarify forces. We first solve for the optimal contract when a is constant to highlight appropriability's effect. We then allow a to vary according to (3.3), allowing the contract to account for investment feeding back into the value of specialists' outside option.

3.3.1 First-Best Benchmark

First-best is achieved when $\lambda = 0$ for then specialists always exert effort. Because the economic environment is *iid* and the model is homogeneous in intangible capital, there is a constant intangible investment rate that maximizes firm value per unit of intangible capital:

$$p^{FB} = \max_g \frac{Z - c(g)}{r - (g - \delta_N)}.$$

Because specialists are relatively more impatient ($\gamma > r$), it is optimal to pay them w immediately, so the payoff to investors per unit of intangible capital is $p^{FB} - w$.

Note these results hold true regardless if the agent can appropriate capital because appropriation only affects the value of their outside option, which they never exercise in first-best. That is, agency conflicts must exist for appropriation to have an economic effect.

3.3.2 The Optimal Contract with Agency

We now solve for the optimal contract and the solution to (3.4). Recall that the contract is a triplet, $C = (g, U, \tau)$, that specifies investment, compensation, and termination. Specialists' continuation payoff W_t is a state variable which summarizes their current incentives and reflects their expected path of current compensation and the likelihood of contract termination; intangible capital captures the history of investment via (3.2); and specialists' outside option is influenced by a. Altogether, whatever the history of the firm up until date t, the only relevant state variables are a_t, N_t, and W_t and, therefore, investors' value function at time t, $P(a_t, N_t, W_t)$, can be solved with a Hamilton-Jacobi-Bellman (HJB) equation.

Incentive Compatible Contract

We focus on the incentive compatible contract that implements $e_t = 1$ for all t. Given this contract and the firm's history up until time t, specialists's continuation payoff is

$$W_t(C) = \mathbb{E}_t \left[\int_t^{\tau} e^{-\gamma(s-t)} dU_s + e^{-\gamma(\tau - t)} W_0(a_\tau, a_\tau N_\tau) \right].$$

Standard theory in dynamic contracting decomposes managers' incremental total compensation into incremental payments dU_t and incremental continuation payoff dW_t (Spear and Srivastava, 1987). When intangible capital can be contracted upon, we formulate managers' incremental total compensation with a martingale representation (see Sannikov (2008) for details):

$$dW_t + dU_t = \gamma W_t dt + \beta_t N_t \left(\frac{dN_t}{N_t} - (g_t - \delta_N) dt \right) = \gamma W_t dt + \beta_t N_t \sigma_N dB_t. \tag{3.5}$$

The incentive coefficient $\beta_t > 0$ serves to expose specialists' compensation to the realizations of intangible capital and is key to maintaining incentive compatibility. Managers who deviate reduce their compensation by $\beta_t g_t N_t dt$ and receive private benefits $\lambda g_t N_t dt$; incentive compatibility is thus implemented with $\beta_t \geq \lambda$ for all t. Because termination is ex post inefficient and therefore costly to enforce, the optimal contract minimizes the likelihood of this event and sets

$$\beta_t = \lambda \text{ for all } t. \tag{3.6}$$

The incentive coefficient, β_t, is thus set to minimize the necessary level of incentive provision.

Once specialists' current wealth hits this lower bound they are better off shirking and consuming private benefits, and because investors know this, they will optimally terminate the contract at this threshold. Since this decision holds continuously, specialists' departure satisfies an indifference condition

$$\underline{W}(a_t, N_t) = W_0(a_t, a_t N_t), \tag{3.7}$$

where $\underline{W}(a_t, N_t)$ is a lower bound on specialists' wealth that is dependent on the level of intangible capital and their skill where it is optimal to terminate the contract.

Homogeneity further allows us to write $p(a, w) = P(a, N, W)/N$ and reduce the problem to two state variables: specialists' skill a and stake $w = W/N$ (their scaled continuation payoff), which evolves, by Ito's lemma, as

$$dw_t = d(W_t/N_t) = \left[(\gamma - (g_t - \delta) + \sigma_N^2) w_t - \sigma_N^2 \lambda \right] dt - du_t + \sigma_N (\lambda - w_t) dB_t, \tag{3.8}$$

where current payments to managers per unit of intangible capital are $du = dU/N$. We also scale the outside option in (3.7) and define

$$w(a_t) \equiv \frac{W(a_t, N_t)}{N_t} = \frac{a_t W_0(a_t, a_t N_t)}{a_t N_t} = a_t w_0(a_t).$$

Subject to the incentive constraint in (3.6), investors optimally choose investment to equate expected returns to their required rate of return, the risk-free rate:

$$rp(a,w)dt = \max_g (Z - c(g))dt + \mathbb{E}_t \left[d(Np(a,w))/N \right].$$

This equation's solution is jointly determined with the boundaries, described below, that determine contract termination and current payments to managers.

3.3.3 Constant Appropriability

We first consider the case where a is constant to provide intuition behind the mechanisms of the optimal contract. We then examine the solution in the more general case where a is dynamic.

Compensation and Termination Boundaries

When a is constant, the only state variable is specialists' stake, $w = W/N$, and investors' value function takes the form of an ordinary differential equation subject to the boundaries below. In Appendix C.1 we show how the model's termination boundary could be determined in a search market. Our model of appropriation thus has a natural connection to the search literature.

As mentioned, specialists will be terminated immediately once their continuation utility reaches the value of their outside option, because otherwise they would immediately consume private benefits; therefore,

$$p(w) = p(aw_0) = l. \tag{3.9}$$

This equation is telling. It succinctly captures the model's primary tradeoff of competing interests and determines the threshold at which the contract terminates. As management's outside option becomes more valuable, through skill a or through bargaining w_0, so does the level of wealth they require to remain in the current firm. Once their current wealth w_t falls and hits aw_0 from above, the value of the firm to investors equals their outside option: liquidation of intangible capital at price l. Naturally, if a goes to zero, the agent has no meaningful outside option and the firm liquidates when $w_t = 0$.

Next, investors can always compensate specialists with cash ($du > 0$), so it will cost at most one dollar to increase w by one dollar, implying $p_w(w) \geq -1$. But because termination is costly to investors it will be optimal to grow w at low values as quickly as possible by setting du in (3.8) to zero. Impatient specialists will eventually require current payments, however. This creates a tradeoff that is determined by the point at which investors are indifferent between paying them a dollar directly and promising them another dollar: $p(w) = p(\overline{w}) - (w - \overline{w})$, where $w - \overline{w}$ is the current payment to keep promised compensation at $\overline{w}$. Continuity implies this equation holds as $w \to \overline{w}$; therefore

$$p'(\overline{w}) = -1, \tag{3.10}$$

and because this is chosen by investors it satisfies the optimality condition

$$p''(\overline{w}) = 0. \tag{3.11}$$

To summarize, $du = 0$ within the payment and termination boundaries and $\beta_t = \lambda$ for all t. With the dynamics of specialists' payoff given, the solution to investors' problem in (3.4) on $w \in [w, \overline{w}]$ takes the form

$$rp(w) = \max_g Z - c(g) + p(w)(g - \delta_N) + p'(w)(\gamma - (g - \delta_N))w + \frac{1}{2}p''(w)\sigma_N^2(w - \lambda)^2 \tag{3.12}$$

subject to the boundaries (3.9), (3.10), and (3.11). This problem is similar to the one studied in He (2009). He shows that relative impatience and optimal contracting requiring the equality of marginal benefits and costs implies the existence of a unique upper bound on w, $\overline{w} < \lambda$.

The first-order condition for the investment rate of intangible capital is

$$c'(g) = p(w) - p'(w)w. \tag{3.13}$$

When choosing investment, investors internalize its effect on specialists' incentives. For a given W, a growth in capital N reduces specialists' effective claim on the firm $w = W/N$, aggravating the agency friction.

Illustration of Model Mechanisms

Before solving for the optimal contract when appropriation is dynamic, we first review and illustrate the intuition behind the model's properties and highlight its novelties while assuming that a is constant. We show how the co-dependence of specialists' and investors' value functions on w_0, the contract's initial relative wealth allocation to agents, affects the form of the optimal contract.

More specifically, Figure 3.1 illustrates how specialists' skill a and bargaining power influence the solution to the investors' problem. The four figures highlight the tension of competing interests and the impact of mobility on investment that we aim to capture in our model. We first focus on the left two figures assuming a low agency cost parameterization. In the top-left panel, we plot investors' value function $p(w)$ as a function of specialists' stake w for three cases. All three value functions at the contract termination boundary equal their liquidation payoff, l.

Two forces, common to DeMarzo et al.'s (2012) model, determine the shape of $p(w)$. Initially as w grows from the lower boundary, the severity of the agency conflict falls, thus raising firm value to investors. To further alleviate the agency friction, however, investors must promise a larger and larger share of the firm to specialists, and therefore $p(w)$ begins to decline, reflecting this wealth transfer. Eventually, its slope becomes linear and equal to negative one at the payment boundary. Despite risk neutrality, investors' value function is concave as investors internalize the risk that the optimal contract places on specialists' actions. The case when $a = 0$ essentially mirrors the benchmark result of DeMarzo et al. (2012).

We then increase a to 0.4. The basic intuition is that greater skill allows the specialist to appropriate more of the stock of intangible capital, thus muting investor value relative to the case with no appropriation and affecting the optimal share of wealth provided to the specialist. In this case, we look at two extremes of bargaining power. When investors have all power, the termination boundary increases to aw_0, where $w_0 =_w p(w)$. This boundary follows from the condition in (3.9) and highlights our novel co-dependency across value functions: specialists' skill a impacts the lower boundary aw_0 that, in turn, affects the location of the maximum of investors' value function, w_0. In contrast, granting managers all power further shifts the boundary rightwards to $a\overline{w}$, where $\overline{w} = w_0 = \max\{w : p(w) \geq 0\}$ here. Yet again co-dependence affects contract value. Here, specialists' skill a impacts that lower boundary $a\overline{w}$ that now affects the placement of specialists' maximum attainable value, $\overline{w}$. Hence, both investors' *and* specialists' maximum values, and more generally the shape of the contract, are affected by bargaining.

Another perspective on bargaining's effect can be seen by fixing w and enhancing specialists' option value. Investors' value function $p(w)$ falls, reflecting a loss in their wealth. This is not a wealth transfer, however, because total firm value $p(w)+w$ actually falls. In effect, greater bargaining power has made it more difficult to incentivize agents for a given w—the agency conflict has been exacerbated, lowering firm value.

We plot the investment rate of intangible capital, g, in the bottom-left panel. Better outside opportunities for specialists lowers the marginal return to investors on intangible capital. This pares investment. The smaller return reflects both a lower average value per unit of capital $p(w)$ and an aggravation of principals' and agents' separate interests, $p'(w)$. To maximize growth, then, is to maximize investors' share of rewards. This is the traditional prescription of Arrow (1962).

Turning to the right panels, we see the polar perspective when we increase λ. Intuitively, the cost of providing deferred compensation to specialists' has grown. Their outside option acts as a lower bound to their compensation, which is valuable to them, so when reducing their skill or when shifting bargaining power to investors, their incentive to work falls. Thus in this case, reducing managers' outside option aggravates the agency friction, which in turn flattens capital's average value and consequently its return on investment. The prescription here is to ensure managers are adequately compensated and retain the value of their outside option, precisely the opposite prescription to the traditional view.

3.3.4 Dynamic Appropriability

We now consider the environment where investment creates knowledge that becomes inalienable to managers and the appropriation process follows (3.3). The payment boundaries on specialists' stake, w, are similar to the case of constant appropriability but now also depend on their skill; namely, for all a

$$p(a, w(a)) = p(a, aw_0(a)) = l \qquad p_w(a, \overline{w}(a)) = -1 \qquad p_{ww}(a, \overline{w}(a)) = 0, \tag{3.14}$$

and, as the problem has two state variables, another optimality condition follows from differentiating the middle equation in (3.14) with respect to a,

$$p_{wa}(a,\overline{w}(a)) = 0 \text{ for every } a. \tag{3.15}$$

We now determine the threshold at which highly skilled agents will be convinced to not leave the firm by means of a retention payment. As before in the case with specialists' stake, this threshold will be determined by comparing agents' relative impatience with the likelihood of costly termination.

Suppose that a specialist's skill, a, rises for a given deferred compensation level, w. Because relative impatience is fixed yet the likelihood of costly termination rises with skill, there again will be a threshold where it will be optimal to pay him or her current compensation rather than to let them leave the firm. Formally, there exists a skill level, $\overline{a}(w)$, above which the specialist will be paid immediately and where investors' decision will satisfy the indifference condition

$$p(a,w) = p(\overline{a}(w),w) - (a - \overline{a}(w)), \text{ for } a \geq \overline{a}(w) \text{ for each } w. \tag{3.16}$$

The point of this current compensation is retention. We give two interpretations to this upper bound. One is that the opportunity to leave is fleeting. The specialist uses the offer to negotiate a bonus with the current firm, discarding the job opportunity. Alternatively, it could be interpreted as a specialist purposefully restricting their marketability in exchange for compensation today, perhaps by setting out to codify some of their knowledge for their current firm to keep or else by publishing work under the company name.

Because specialists can leave the firm and raise a_t dollars per unit of capital, investors optimally pay them $a_t - \overline{a}(w_t)$ immediately to retain them and avoid the cost of liquidation. In words, specialists appropriate everything along the retention boundary when their skill increases. Retention payments, moreover, are proportional to the difference $a_t - \overline{a}(w_t)$. Higher skilled specialists get paid more. Additionally, because specialists are relatively impatient, they prefer current compensation to deferred compensation.

Next, we can use the continuous properties of our model to simplify the conditions above. For each w, as we take a to $\overline{a}(w)$ we get

$$p_a(\overline{a}(w), w) = -1 \qquad\qquad p_{aa}(\overline{a}(w), w) = 0. \tag{3.17}$$

As before, optimality produces the right equation and our two-state problem further requires that the derivative of the left equation by w satisfy

$$p_{aw}(\overline{a}(w), w) = 0 \text{ for every } w. \tag{3.18}$$

And finally, from (3.15) and (3.18) and Young's theorem it is evident that

$$p_{aw}(\overline{a}(w), \overline{w}(a)) = 0 \text{ for every } a \text{ and } w. \tag{3.19}$$

We obtain insight on the optimality condition by specializing (3.16) to the case where $w = w(a)$ and taking the limit $a \to \overline{a}(w)$:

$$\begin{aligned} p(a, w(a)) &= p(\overline{a}(w), w(a)) - (a - \overline{a}(w)) \\ &= l - (a - \overline{a}(w)) \\ \Rightarrow \lim_{a \to \overline{a}(w)} p(a, w(a)) &= p(\overline{a}(w), w(a)) = l. \end{aligned} \tag{3.20}$$

Thus, the boundary where specialists' skill approaches $\overline{a}(w)$ when $w = w(a)$ are those where investors understand the imminent threat of agents leaving the firm, causing firm value to near the liquidation value. Moreover, a similar approach that first sets a to $\overline{a}(w)$ and then takes the limit $w \to w(a)$ also produces a value of l in (3.20). Therefore, there is an equivalence as the lower boundary for specialists' stake, $w(a)$, equals the upper boundary for specialists' skill, $\overline{a}(w)$.

We emphasize that our model provides two sources of current payments or bonuses to specialists. One is the traditional one of maintaining incentive compatibility in the presence of impatient agents, similarly to DeMarzo et al. (2012); this is $\overline{w}(a)$. Our novel channel comes from retention; that is when $\overline{a}(w)$ is crossed from below when an agents' skill becomes more valuable. In contrast to the payments "for impatience" which occur at high w, retention payments could occur at low w.

Hamilton-Jacobi-Bellman Equation and Investment

To summarize, $du = 0$ within the payment and termination boundaries and $\beta_t = \lambda$ for all t. Assuming the contract always prescribes full effort, the solution to investors' problem in (3.4) takes the following form subject to the boundaries in (3.14), (3.15), (3.17), (3.18), and (3.19):

$$
\begin{aligned}
rp(a,w) = \max_g\, & Z - c(g) + p(a,w)(g - \delta_N) \\
& + p_w(a,w)(\gamma - (g - \delta_N))w + \frac{1}{2} p_{ww}(a,w)\sigma_N^2 (w - \lambda)^2 \\
& + p_a(a,w)\kappa(g - \delta_N)a + \frac{1}{2} p_{aa}(a,w)\sigma_a^2 a^2. \qquad (3.21)
\end{aligned}
$$

We describe our computational procedure to solve this equation in Appendix C.1. In the appendix we also show that, in our calibration of Section 3.5, it satisfies both contract optimality and the implementation of full effort by specialists.

The first-order condition for investment becomes

$$
c'(g) = p(a,w) - p_w(a,w)w + p_a(a,w)\kappa a, \qquad (3.22)
$$

and, relative to (3.13), is now influenced by its effect on specialists' skill. Intuitively, because investment in intangible capital is not wholly captured by investors, the term $p_a(a,w)\kappa a$ captures how much of investors' firm value is lost by specialists' gaining skill and raising the value of their outside option. This term reflects the thinking of Arrow (1962).

We provide perspective on the conditions of (3.17) by applying them to the HJB equation and rearranging it:

$$
\begin{aligned}
rp(\overline{a}(w),w) = \max_g\, & Z - c(g) - \kappa(g - \delta_N)\overline{a}(w) + p(\overline{a}(w),w)(g - \delta_N) \\
& + p_w(\overline{a}(w),w)(\gamma - (g - \delta_N))w + \frac{1}{2} p_{ww}(\overline{a}(w),w)\sigma_N^2 (w - \lambda)^2. \qquad (3.23)
\end{aligned}
$$

In effect, there is an extra cost that investors must pay at the retention boundary equal to $\kappa(g-\delta_N)\overline{a}(w)$. Intuitively, the firm makes a retention payment equal to the immediate appropriation of the firm's intangible capital by specialists. Highly skilled agents are more costly to retain, resulting in lower investment. This prediction agrees with the empirical results of Fedyk and Hodson (2022).

Total Compensation

We define *total compensation* as the sum of deferred compensation plus the current compensation received when $w_t > \overline{w}(a_t)$ and $a_t > \overline{a}(w_t)$ and, respectively, split the sources of current payments u_t into the variables u_{wt} and u_{at}. Per unit of intangible capital it thus follows the process

$$w_t^{\text{total}} = w_t + u_{wt} + u_{at}.$$

This process has the properties that (i) u_{wt} and u_{at} are increasing and continuous with $u_{w0} = u_{a0} = 0$, (ii) $w_t = w_t^{\text{total}} - u_{wt} \in [\underline{w}(a_t), \overline{w}(a_t)]$ for all $t \geq 0$ and $w_t = w_t^{\text{total}} - u_{at} \in [0, \overline{a}(w_t)]$ for all $t \geq 0$, and (iii) u_{wt} only increases when $w_t = \overline{w}(a_t)$ and u_{at} only increases when $a_t = \overline{a}(w_t)$. These properties imply that w_t is a regulated Brownian motion with time-varying controls at $\overline{w}(a_t)$ and $\overline{a}(w_t)$.

Following Harrison (1985), we substitute out u_{wt} and u_{at} from the above equation replace them with primitive model elements. Doing this, we obtain

$$w_t^{\text{total}} = w_t + \max\left(\sup_{0\leq s\leq t}(w_s^{\text{total}} - \overline{w}(a_s)), 0\right) + \max\left(\sup_{0\leq s\leq t}(w_s^{\text{total}} - \overline{a}(w_s)), 0\right)$$

and draw two observations.

First, total compensation, which can be measured, albeit imperfectly, in the data, reflects a combination of deferred and current compensation. We therefore define compensation accordingly in the data.

Total compensation, moreover, depends on the history of agents' skill through the terms $\sup_{0\leq s\leq t}\overline{w}(a_s)$ and $\sup_{0\leq s\leq t}\overline{a}(w_s) = \sup_{0\leq s\leq t} w(a_s)$, where equality follows from the equivalence shown in (3.20). Because in our model specialists' outside option is monotone in a, $w'(a) > 0$, we can proxy for appropriability in the data with a measure of specialists' outside options. We construct this measure in Section 3.4 and further use it to examine the dynamic contracting implications of our theory in Section 3.5.

Stationary Distribution

As we have seen, the threat of contract termination is a salient force that shapes agents' incentives and intangible capital accumulation. A given contract will be eventually terminated with probability one. To have a stationary distribution of contracts, firms, and workers, we allow for entry. We use this distribution to compute model statistics that we compare with the data.

The stationary distribution $h(a,w)$ satisfies the equation

$$0 = \mathcal{A}^* h(a,w) + \psi(a,w)m,$$

where $\mathcal{A}^* h(a,w)$ is the adjoint of the infinitesimal generator of the bivariate diffusion process (da, dw), which intuitively captures the transition rates generated by the dynamics of the model's state variables under the optimal policies.[7] By construction this generator contains the rates of exit that occur along the termination boundary, $w(a)$, and so to ensure a stationary mass of firms, we add a product of an entry rate, m, and an entry mass, $\psi(a,w)$, which integrates to one.

We normalize the total mass of firms to one, $\iint h(a,w)dwda = 1$, where the implying that the stationary entry rate equals

$$m = -\iint \mathcal{A}^* h(a,w)dwda.$$

When a specialists' contract is terminated we assume that a fraction $\zeta \in (0,1)$ of them start new firms with intangible capital $a_t N_t$. The remaining $1-\zeta$ replaces the exiting specialist with a draw from a skill distribution with positive support, which allows for the model to incorporate uncertainty in the quality of the match of the new specialist-firm pair. The entrant, moreover, also starts with a new continuation payoff, w_0, determined by agents' and investors' bargaining powers.

[7] Specifically, we calculate this with the transpose of the discretized transition matrix **Q** in Appendix C.1.

3.4 Empirical Setup Used to Discipline Model Calibration

The evolution of specialists' skill is key to the mechanisms of the model. The parameters that govern its evolution, however, are unobservable. There is therefore a challenge in determining reasonable values for the parameters that measure the rate of appropriation, κ, and the variation in marketability, σ_a. To make progress on this issue, we exploit the model property that specialists' outside option $\overline{w}(a)$ is monotonically increasing in a. Hence, measurements of outside options in the data allow us to infer the behavior of skill in the model.

In this section, we present new evidence on how specialists' incentives and firms' policies respond to the value of specialists' outside options and their mobility. We use this evidence to discipline the calibration of our model, specifically the key unobserved parameters, κ and σ_a, governing the appropriation equation (3.3).

3.4.1 Empirical Environment

We first construct a value for the outside options of the firm's specialists. We then devise an empirical environment to provide shocks to those options' values and identify its effect on a range of outcomes, most importantly the rate of specialists' turnover and firms' intangible investment rates.

We define two types of specialists: the chief executive officer (CEO) and employees of "high-skilled" industries.[8] We examine chief executives partly due to the availability of more complete data but also because they are known to play an outsized role in the creation of a firm's capital. We supplement with a separate examination of the prospects of high-skilled employees. The results from both types are useful for our calibration because, according to our model, the impact of appropriation on investment will be similar across both types as long as the share of deferred compensation relative to total compensation is comparable across types.

[8] We follow Brown et al. (2009) and define these industries as in NAICS = 51 (Information), 52 (Finance and Insurance), 53 (Real Estate and Rental and Leasing), 54 (Professional, Scientific, and Technical Services), 55 (Management of Companies and Enterprises), 61 (Educational Services), and 62 (Health Care and Social Assistance).

Value of Outside Options

We measure specialists' outside options following the methodology of Schubert et al. (2019) by constructing a weighted sum of average compensation at the industry-state-year level:

$$\text{Outside Option}_{j,s,t} = \sum_{j' \in J} \pi_{j \to j'} \overline{w}_{j',s,t}. \tag{3.24}$$

The variable Outside Option$_{j,s,t}$ measures the value of outside options that specialists' possess whose firms are located in industry j and state s in year t.

The unconditional transition probability $\pi_{j \to j'}$ reflects the likelihood that a specialist leaves industry j to join industry $j' \in J$, where J is the set of all industries. We estimate this probability by tracking the fraction of all specialists who have left industry j to join j' and averaging across all years. We then multiply this probability by the average specialist compensation in that state-industry-year, $\overline{w}_{j',s,t}$. Altogether, a specialist's outside option will be more valuable the greater the compensation that specialists earn in other states and industries, $\overline{w}_{j',s,t}$ and the more frequent that specialists leave and take jobs in other industries, $\pi_{j \to j'}$.

The logic behind (3.24) is that an agent's outside option is a function of i) compensation in a given industry in a local labor market (defined as a state in our setting), and ii) the mobility across occupations. Mobility is captured by the transition matrix and reflects the rate of job flows but doubles as an implicit metric of costs associated with changing occupations. These costs represent a broad notion and could reflect many things, including the loss of moving away from family or neighborhood, the uncertainty attributed to a new job, or also proxy for (inverse) market tightness, a salient equilibrium object featured in the class of search-theoretic models of the labor market (Rogerson et al., 2005).

Shocks to Outside Options

With this measure of outside options in hand, we entertain shocks to these options. We derive our shocks by exploiting variation in the degree of enforcement of non-compete agreements.

Non-compete agreements (NCAs) are contracts signed between employees and firms that prohibit employees from joining or forming a competing firm. Their purpose is to protect a given firm's intellectual property from direct competition, thus facilitating the retention of economic rents that, hopefully, encourages more innovative activity. These contracts, however, also restrict the outside options of employees by diminishing their ability to take jobs at other firms. They are widely known to be applicable to our definition of skilled employees. Jeffers (2020), for example, documents that these agreements affect a large set of workers, and are especially prevalent for workers in knowledge-intensive industries. Shi (2022) reports that 64 percent of chief executives are subject to these agreements.

We measure the degree of enforcement of NCAs by using the non-compete enforceability index (NCEI) of Garmaise (2011), which is constructed at the state-level from a sample of twelve questions with thresholds devised by Malsberger (2004) from 1992 to 2004.[9] We use Kini et al.'s (2021) data to extend the NCEI sample to 2014. The index counts each answer that surpasses a threshold and ranges from zero (the most lax) to twelve (the most restrictive).

Figure 3.2 depicts substantial heterogeneity within the unconditional state-year distribution of the NCEI for our sample. The index, moreover, may change for a given state as a result of litigation or new laws being passed that impact non-compete agreements. We use both sources of variation to derive the shocks used in our empirical analysis.

The first source, *NCEI*, is the value of the index in a given year for the state in which a firm is headquartered. The second source follows Garmaise (2011) and is a categorical variable based on the change in the index, $\Delta NCEI$, that takes a value of 1 if the state a firm is located in has an *NCEI* value that is greater than its initial 1992 value in a given year, a value of -1 if the value is lower than its initial 1992 value in a given year, and a value of zero if it is the same as its initial value. As noted by Kini et al. (2021) and others, these state-level changes to enforcement are likely unanticipated when contracts were written, and thus can be viewed as exogenous shocks at the firm level to the strength of non-compete agreements.[10] In line with

[9] For example, the first question asks whether there is a state statute that governs the enforceability of covenants not to compete. Almost all states other than California and North Dakota permit some form of non-compete agreements. The remaining questions sift through contractual details of enforcement. As two examples, the second question asks whether the employer can prevent the employee from future independent dealings with all the firm's customers, not just those with whom they had had previous contact; the ninth question asks what type of time or geographic restrictions has the court found to be reasonable.

[10] Consistent with this, Jeffers (2020) manually examined court rulings related to the enforcement of NCAs, and finds that these judicial decisions were unlikely associated with political concerns related to the re-appointment or re-election of judges. She and Ewens and Marx (2018) also argue that state bills affecting the enforcement of NCAs were either subject to substantial uncertainty or were not explicitly lobbied for by companies.

the validity of this assumption, we further show that outside option values exhibit no discernible pre-trends prior to changes in the NCEI, but then change only after changes in the NCEI.

Empirical Specification

Our empirical strategy takes the form of an instrumented difference-in-difference regression. In particular, we first instrument for specialists' outside option using our shocks, the state-level variation in the enforceability index. We then estimate the impact of the instrument on the firm's intangible investment and their likelihood of leaving the firm.[11] Our identifying assumption is that changes in the enforcement of NCAs affect firm intangible investment and turnover only through their impact on specialists' outside options.

Formally, our first-stage regresses specialists' outside option value on their states' NCEIs, firm-level controls, and a set of fixed effects:

$$\log \text{Outside Option}_{j,s,t} = b_1 \text{NCEI}_{s,t} + B_1 \text{Controls}_{i,t-1} + f_i + f_t + \epsilon_{i,j,s,t}. \tag{3.25}$$

We measure the outside option, $\log \text{Outside Option}_{j,s,t}$, as the logarithm of one plus the outside option value for firms in state s and industry j in year t, as defined in (3.24). The variable NCEI is either $NCEI_{s,t}$ or $\Delta NCEI_{s,t}$. Firm fixed effects, f_i, are included to control for time-invariant heterogeneity between firms and year fixed effects, f_t, for time trends. With the inclusion of fixed effects, equation (3.25) captures changes to the outside options of specialists induced by shocks to the enforcement of NCAs in the states in which their firms are located.

We then use the regression's predicted value, $\log \widehat{\text{Outside Option}}_{i,j,s,t}$, which varies with firm-level characteristics, as an instrument in our second-stage regression to study the response of our outcomes of interest, $y_{i,t}$,

$$y_{i,t} = b_2 \log \widehat{\text{Outside Option}}_{i,j,s,t} + B_2 \text{Controls}_{i,t-1} + f_i + f_t + \epsilon_{i,j,s,t}. \tag{3.26}$$

[11] The point estimates from our instrumented differences-in-differences regression best corresponds with the sensitivities of our model, as this regression estimates the *local* average treatment effect for a firm whose specialists' outside options are changed by non-compete enforcement. An alternative strategy would be to run a reduced-form regression that examines the effect of NCEI changes on outcomes directly. This would provide an estimate of the average treatment effect on the outcome variables attributable to changes in NCEIs. See Hudson et al. (2017) for a discussion of this distinction. We find equivalent results with this specification.

We separately estimate (3.25) and (3.26) for our two types of specialists. For our specifications involving chief executives, we construct our outside option measure using average CEO wages and transition probabilities between industries for chief executives. For high-skilled employees, we build our measure using average wages of workers in high-skilled industries in a given state, and transition probabilities for workers between industries. Due to the structure of our datasets, our transition probabilities are calculated at the two-digit SIC level for CEOs and at the two-digit NAICS level for high-skilled workers.

We examine intangible investment rates for both types and turnover only when using our specification that involves chief executives. Our data do not permit us to track turnover for high-skilled employees at the firm-level.

3.4.2 Data and Summary Statistics

Our sources draw from databases on public firms' financial reports, particularly their accounting and compensation data, US Census data on employment and job-to-job flows, and the aforementioned state-level regulatory changes in the degree of employment contract enforcement. We discuss these in turn before describing interpreting our empirical results.

Compensation, Turnover, and Outside Options

Our chief executive compensation and turnover data come from Compustat's Execucomp database. We use the variable $tdc1$ that includes salary, bonuses, and deferred compensation in the form of equity and options at the time of granting. We apply Gillan et al.'s (2018) filter to remove back-filling bias.

Our turnover variable is an indicator that becomes active the first year a firm's CEO leaves office, if ever. We then apply Gentry et al.'s (2021) detailed classification of departures to exclude impertinent cases such as company name changes, mergers or acquisitions, bankruptcies, interim executives, Execucomp misreporting, and departures without media or regulatory filings.

The data for calculating the values of outside options for high-skilled workers comes from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW) database and the US Census's Job-to-Job Flows database, part of the Longitudinal Household-Employer Database. These datasets collectively contain variables on wages and worker transition rates at the industry-state-year level. We calculate the average wages of employees for each NAICS industry in each industry-state-year and multiply them by industry-to-industry transition rates to for our outside option value for high-skilled employees.

Intangible Investment and Firm-Level Data

We then use Compustat's accounting data to build our measures of intangible investment and other firm-level control variables. We measure intangible investment in two ways. The first follows recent practice in the literature that capitalizes intangible investment with a perpetual inventory method (Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013)). Specifically, we construct the level of intangible capital for firm i in year t, $N_{i,t}$, as a function of selling, general, and administrative expenses ($SG\&A$):[12]

$$N_{i,t} = (1-0.15)\times N_{i,t-1} + 0.3\times \frac{SG\&A_{i,t}}{CPI_t}, \tag{3.27}$$

where CPI_t is the consumer price index. Following Peters and Taylor (2017) who study this construction in detail, we attribute 30 percent of (real) SG&A expenditure to intangible development, use a 15 percent depreciation rate, and initialize the process at $SG\&A_{i,0}/0.25$. Accordingly, we define intangible capital's investment rate as (3.27)'s right-most term divided by $N_{i,t-1}$.

Our second measure of intangible investment follows Sun and Xiaolan (2019) and uses research and development expense as an alternative measure of intangible investment. We normalize the R&D flow with the lag of intangible capital.

In our regressions, we include a standard set of firm-level regression controls: the lagged investment rate, turnover, cash, profitability, leverage, Tobin's Q, and the lagged logarithm of intangible capital. For our regressions for CEOs, we also include an indicator that takes a value of 1 if firm's chief executive is over 62 years old. We normalize ratios by the level of intangible capital to have common denominators on both sides of our investment regressions. Appendix C.2 defines these variables and provides further details on sample selection.

[12] Compustat's record of SG&A (*xsga*) includes expenditure on research and development, and a large part of this consists of expenses related to training (human capital and business processes), skilled labor (programmers), information technology, as well as marketing (brand capital).

Summaries of Samples

Our sample on CEOs begins in 1992, as this is when Execucomp data become available, and ends in 2014, as this is the latest year for which we have NCEI data. The resulting sample is a panel of 20,291 firm-year observations for 2,063 firms. Our sample of high-skilled employees consists of 1,600 firms across 13,296 firm-year observations and runs from 2000, when the QCEW data begin, to 2014.

For both samples, we exclude 2008 and 2009 from our sample to remove crisis-induced outliers that are unrelated to our analysis.[13] We make all level variables real in 1982 dollars. Appendix Table C.1 provides summary statistics for the key variables in our sample. In addition, we find that conditional on a change in *NCEI* since 1992, the median change is two index values.

3.4.3 Empirical Results

We present our first- and second-stage results in turn. We then discuss robustness.

Impact of Enforceability on Outside Option Value

Table 3.1 summarizes the principal outcomes of our first-stage estimation for executives. Column (1) shows the impact on outside options of the level of index, *NCEI*, while column (2) lists the point estimate from the change, $\Delta NCEI$. The coefficients of interest are significant and the F-statistics of both regressions are much larger than ten, indicating that the instrument satisfies the relevance condition.

Common to both enforcement variables, a strengthening of the NCEI leads to a reduction in the value of a given executive's outside option. Column (2), for example, implies that a two-unit change in the non-compete enforceability index reduces the value of a CEO's outside option by 10.6 percent. Such a shift from the sample average is equivalent to over a fifth of a standard deviation across executives. Columns (3) and (4) report the estimates of the impact on the value of the outside option normalized by the firm's intangible capital, metrics that will be useful when we calibrate our model. Column (4) shows that a two-unit change in the non-compete enforceability index reduces the CEO's outside option by 1 percent of firm's intangible capital, which is equivalent to a half of the sample average of 2 percent.

[13]Results are largely unaffected by this restriction that is more in line with our theoretical framework.

Because our first-stage compares firms that have been treated with a change in enforceability to those that have not and because this treatment occurs across states at different points in time, it is a staggered difference-in-difference regression. Consequently for our identifying assumption to hold, the outside option values of specialists for the treated and control firms must move in parallel prior to any change in NCEIs and should diverge subsequent to a change.

Staggering can introduce a discrepancy between the estimated coefficients and the actual average treatment effects when examining parallel trends (see Goodman-Bacon (2020) for details). To address this, we use the methodology in Sun and Abraham (2021) and depict the coefficient estimates in Figure 3.3 using $\Delta NCEI$ for two control groups: the set of firms that are never treated and never experience a change in the enforcement index, and the set of firms that were last treated. We see for both sets of control groups that the parallel trends assumption clearly holds—the treated and control groups move in parallel prior to a strengthening of the NCEI and then the outside option's value for the treated firms drops relative to the control firms after the index changes. The difference becomes significant in the first year after the shock, and the largest reductions concentrate around three to four years afterward.

Executives' Outside Options, Turnover, and Firms' Intangible Investment

With the first-stage established, we now turn to the results of our second-stage regression shown in Table 3.2. Panel A reports the estimates for the instrumented logarithm of the outside option index and Panel B the instrumented outside option over intangible capital. We find that greater values of specialists' outside options reduce intangible investment in their current firm. The estimated effects are statistically significant and have similar economic magnitudes using either column (1)'s *NCEI* or column (4)'s $\Delta NCEI$ as the instrument. In particular, the estimates point to a 10.6 percentage point increase in the outside option index lowering intangible investment by approximately $10.6 \times 0.066 = 70$ basis points per year. Seventy basis points of growth per year is a material impact.

In columns (2) and (5), we use R&D investment as an alternative proxy of intangible investment and find consistent results. Here we find a negative and significant impact on research and development by $10.6 \times 0.169 = 1.8$ percent as a fraction of intangible capital, a fifth of the average R&D investment rate.

We then examine how CEO turnover responds to variation in outside options. Focusing on column

(6), the point estimate shows that a 10.6 percentage point increase in option value raises the likelihood of departure by over $10.6 \times 0.219 = 2.32$ percent. The effects are statistically significant at conventional levels. When considering the economic magnitude, the change accounts for nearly a half of the average turnover rate of 4.7 percent annually. Panel B's results that use the scaled outside option as the focal regressor are consistent with Panel A's. The only exception is that column (3)'s coefficient has a p-value of 0.102.

High-Skilled Employees' Outside Options and Firms' Intangible Investment

In Table 3.3, we report a similar set of regression results when focusing on high-skilled employees. Columns (1) and (4) show the first-stage results when instrumenting for outside options using *NCEI* and Δ*NCEI*, respectively. The point estimates show that a two-unit increase in non-compete enforcement index leads to around a 4.4 percent reduction in the value of these employees' outside options.

In the third row, we produce the second-stage results for investment rates. Consistent with what we found when studying executives, greater values of outside options in high-skilled industries leads to a decrease in the intangible investment rate, although the effect is not statistically significant; when measuring intangible investment via R&D, however, the effect is. The economic significance of the effect across chief executives and skilled employees is moreover similar for R&D investment: a 4.4 percent drop in outside option value, for example, leads to a $4.4 \times 0.419 = 1.84$ percent drop in annual research and development expenditure.

This result is consistent with skilled employees being more crucial for research and development rather than overall intangible investment. This is plausible as chief executives likely have greater control over the firm's total capital rather than just a specific division. Hence, variation in CEO mobility thus affects the whole firm's intangible investment, including its R&D division's. Overall, the results when measuring outside options for workers in high-skilled industries echo what we find when studying chief executives.

Robustness Checks

We do many robustness checks to confirm the validity and generality of our results:

1. A concern is that changes in the NCEI are correlated with aggregate factors that could influence turnover or intangible investment. We note that we include time fixed effects in all of our regressions,

which control for aggregate factors. In Panel B of Appendix Table C.1, we further show that changes in the NCEI exhibit very low correlation with a variety of common aggregate variables.

2. Our specification is an instrumented difference-in-difference. An alternative strategy would be to run a reduced-form difference-in-difference regression that examines the effect of NCEI changes on outcomes In Appendix Table C.2, we show that this reduced-form regression produces consistent results.
3. We run a placebo falsification test for the year of the change in the NCEI to ensure that our results are not driven by contemporaneous trends that coincide with the state-level changes in the NCEI. More specifically, we define a variable, $\Delta NCEI_{false}$, that sets the change defined by $\Delta NCEI$ to occur five years before the actual change in the NCEI. Appendix Table C.3 shows that we find insignificant results with this test, indicating that our results are driven by the actual changes in the state NCEIs.
4. In Appendix Table C.4, we investigate the long-run impact on intangible investment rates. The effects become even stronger, consistent with intangible investment being a long-term and potentially strategic decision. The effects of outside options on intangible investments are quite persistent, remaining significant up to four years after. Specifically, at the four-year horizon, a 10.6 percent growth in the value of an outside option translates to a $10.6 \times 0.627 = 6.6$ percentage point fall in average intangible investment rate of a firm operating in a state that has recently relaxed enforcement by two degrees.
5. Our turnover variable measures the probability that a chief executive leaves the company. In Appendix Table C.5, we follow Graham et al. (2020) and calculate the probability that a CEO will find another executive job after leaving the current position. Their measure of executive mobility also responds intuitively to a growth in the value of their outside options and shares the same sign as our turnover variable.
6. Appendix Table C.6 reports the effects of our outside option index on the rates of firm entry and exit for both public firms as well as public and private firms. The data on public firm entry and exits come from Compustat, while the data on public and private firm entry/exits are from the Business Dynamics Statistics (BDS) of the US Census. Here we do not find much evidence of a robust impact on these rates. This result separates our mechanism from Shi's (2022) as she focuses on the extensive margin whereas we focus on the intensive margin.

7. In line with this, in unreported tests, we also do not find a significant effect on the Herfindahl index defined at the industry-state-year level in response to changes in the NCEI. This indicates that the competitive structure of the industry is not being changed by the shock; for example, by firms relocating in response to changes in non-compete enforcement.

3.5 Calibration and Model Analysis

With our conclusions from our empirical environment drawn, we now calibrate and analyze the model.

3.5.1 Calibration

We divide the parameters into two groups, externally- and internally-calibrated. We tabulate them in Table 3.4 along with the moments targeted by the internal calibration.

For regressions and sorts in the model, we simulate the model 5,000 times at a monthly frequency and aggregate the data to form annual observations. Each simulation contains 1,000 firms and has a length of 20 years after a burn-in to avoid dependence on initial values, giving us an firm-year observation count of 20,000 that is close to the size of our data sample. We average over simulations for point estimates and conditional moments.

External Calibration

We begin with the external parameters and set the annual real interest rate, r, to 4 percent. We use a value of $\delta_N = 15$ percent to be consistent with our definition in (3.27) and the Bureau of Economic Analysis's rate used for research and development. As we are interested in analyzing the long-run steady state of our model, we specify our smooth adjustment cost technology to study the model's long-run properties. Following Hall (2001), we interpret the parameter θ as a doubling time for a capital stock and set it to 20 years.

The threat of termination in the optimal contract is used to ensure agents' proper incentives. The true costs of replacing managers has been little studied. Taylor (2010) provides a structural estimate in a dynamic compensation model of total chief executive firing costs to be 5.9 percent of firm assets. In line with this evidence, we impose $l = 0.94$.

The variability of the growth rate of intangible capital which influences the severity of the agency friction and the likelihood of contract termination. Equation (3.1) shows that the variability of cash flows is directly related to the variability of intangible capital. We equate σ_N to 0.2 to target unconditional cash flow volatility used in previous studies (for example, Gomes (2001b) and Miao (2005)).

Upon contract termination at time t, a fraction $\zeta \in (0,1)$ of matches are good quality and the specialist starts a new firm with capital $a_t N_t$. We set $\zeta = 0.3$, which is the value obtained by Gertler et al. (2020) in their internal calibration targeted to the share of job transitions involving positive wage changes. The remainder $1-\zeta$ obtain a skill draw from a distribution of positive support. We fit a log normal curve to the distribution of skill for all US workers, weighted by individual employment in 1999 from the Bureau of Labor Statistics.[14] The estimates are a mean of -4 and standard deviation of 1.5 and we use those parameters. We then truncate the density so that its support remains compact as in our model.

We assume that the entry mass is conditional on the distribution of these skill levels a_0, $\psi(a_0, w_0) = \psi_w(w_0|a_0)\psi_a(a_0)$. Given the skill draw, the distribution of w_0 is degenerate and depends on investors' and specialists' bargaining power. Following Taylor (2010) who structurally estimates relative bargaining power to be equally split between shareholders and the chief executive, we assume that investors and specialists have equal power: $\psi = 0.5$.

Internal Calibration

As we focus on long-run growth, our internal calibration chooses parameters that are important in determining the shape of stationary distribution as well as entry and exit (turnover) rates. We first calibrate the marginal product of intangible capital to match average profitability and investment rates. In our data sample, the average profitability across all firm-years is 0.042 and this requires $Z = 0.224$. The exogenous growth rate z is calibrated to 0.028 to match our sample's average intangible investment rate of 0.212.

Average rates of contract termination are targeted with the parameter λ that measures the severity of the agency friction. All else equal, a higher value will increase the probability of termination. We calibrate parameter λ to 0.29 to match the sample's average CEO turnover rate of 4.7 percent.

Manager's time rate of preference is $\gamma > r$. Its value influences the length of the interval $[w(a), \overline{w}(a)]$

[14] https://www.bls.gov/opub/mlr/2017/article/wage-and-job-skill-distributions-in-the-national-compensation-survey.htm

for every a. More impatient agents (higher γ) require relatively sooner current payments, lowering $\overline{w}(a)$ all else equal. We convert the agent's stock of compensation w to a flow by multiplying it by γ.[15] Altogether, we parameterize time preference to $\gamma = 0.11$ by calibrating to average compensation in the data, which is 0.018.

We use the results of our empirical environment to discipline key parameters; namely, the appropriability parameter κ and the volatility of the skill shock σ_a. First, given an investment rate $g - \delta_N$, equation (3.3) shows that the parameter κ determines the conditional mean growth rate of appropriation and thus the average value of outside options. Hence, investment is informative about appropriability. Second, Variation in a and thus in the value of outside options, $\underline{w}(a)$, influences the likelihood of turnover.

We target these two parameters with indirect inference. Specifically, we run panel regressions in each simulation to replicate the coefficients obtained in our empirical regressions:

$$g_{it+1} = f_i + \beta_g \times \underline{w}(a_{it}) + u_{it+1} \tag{3.28}$$

$$\mathbf{1}\{w_{it+1} < \underline{w}(a_{it+1})\} = f_i + \beta_w \times \underline{w}(a_{it}) + v_{it+1}, \tag{3.29}$$

where f_i are firm fixed effects, u and v errors, and β_g and β_w the target coefficients. As in the data, we regress the investment rate and an indicator for turnover on the outside option value and include firm fixed effects. The stationary economy obviates the need for year fixed effects. We set the values $\kappa = 0.4$ and $\sigma_a = 0.035$ to match Table 3.1's coefficients.

3.5.2 Numerical Solution and Model Analysis

Figure 3.4 shows the top-down view of investors' value function as a function specialists' skill a and stake w. Greater values correspond to lighter (hotter) colors. The form of the sail-shaped figure is determined by (3.21)'s maximum in conjunction with the attainment of the optimal boundaries described in Section 3.3.

The calibrated model places the greatest value to investors in the bottom-right of the state space. Consequently, the stationary distribution will place a large mass in this region where low skills but high stakes are observed. There is thus a compromise: investors keep the risk of appropriation small and, in concession,

[15] This conversion is consistent with a dynamic contracting model with an agent whose consumption-savings decisions are invariant to wealth effects, for example with CARA utility. See He (2011) and Ward (2022).

give specialists a large stake in their firm.

The bottom boundary, along which $a \geq 0$, is reflecting. The right boundary is the impatience boundary $\overline{w}(a)$. Starting from $a = 0$, it initially rises and shifts out and to the right with a as it is optimal to reduce the likelihood of termination. At some point, however, the probability that a high-skilled specialist will leave is too great and motivating them with deferred compensation is too costly, thus bringing the boundary back in and to the left. The boundary where specialists leave the firm, $w(a)$, coincides with the boundary where they are paid retention payments, $\overline{a}(w)$. In accordance with the equivalence shown in (3.20), investor value equals l all along these overlapping boundaries. Specialists with skill along the very top of the sail and who experience positive skill shocks receive retention payments at all levels of w.

Two black lines overlay the figure. The first is dotted and tracks the maximum of the value function for each a. We see that at low values of skill the maximum lies in the interval $[w(a), \overline{w}(a)]$ but when $a > 1$ it lies on the lower boundary $w(a)$. This depicts the continuous transition from a "low agency cost" to a "high agency cost" environment that we saw in Figure 3.1.

The second line is dashed and equals $a\overline{w}(a)$. In the special case where specialists were to have all bargaining power, the value function would lie completely below this line as this is how the lower boundary $w(a)$ would be determined. We see that part of the value function lies above it for a given w, reflecting the expansion of the contracting space by giving some bargaining power to investors.

As in DeMarzo et al. (2012), investors' scaled value function $p(a,w)$ is concave in specialists' stake w. For a given a, investors' value to the right of the dotted line decline, a result of wealth transfers from investors to specialists to provide sufficient incentive for them to continue working. What is new is that the value function declines in a for a given stake. Greater skill raises the probability of costly termination as it becomes more likely a valuable agent will leave. Investors' value consequently is reduced as it becomes more costly to motivate agents.

Distribution of Outside Options

To further verify our model's ability to match the data, we compare distributions of outside options, something not targeted in our calibration. The variable being compared is an executive's value of outside options divided by their firm's intangible capital, $W(a)/N$.

We make two adjustments before doing so. First, we convert the model's numbers to a flow by multiplying $w(a)$ by γ, consistent with our treatment of compensation and the measurement in the data. Second, in the model when a specialist leaves they find a new firm with probability one. In the data, not all find a new job immediately. Consequently, we adjust the empirical option value by multiplying by the probability of finding a job conditional on leaving one, which is 7.75 percent in the data for chief executives.

After these adjustments, we compare the stationary distribution of scaled outside options in the model to our empirical measure in Figure 3.5. We see that the model's marginal distribution of outside options is clustered near zero and has a long right tail, as in the data—being truly highly skilled is a rarity. On the whole, the model fit is very close.

Outside Option Quintiles and Model Predictions

We turn to examining the model's predictions for compensation, turnover, and investment and how they vary with the distribution of outside options. Each year in both model and data, we rank executives by their scaled outside options $\gamma w(a)$ sort them into quintiles. We then equally-weight various statistics within each quintile and repeat the process every year. Because specialists' skill is monotone in their outside option, $w'(a) > 0$, our non-parametric sorts on options are equivalently sorts on skill.

We tabulate each quintile's time-series average across in Table 3.5. Panel A reports the data and Panel B reports the model. In both panels, the value of specialists' outside options per unit of intangible capital increases along these quintiles, rising from near zero all the way to 91 basis points in the data.

We first analyze compensation. Compensation grows with outside option values in both model and data. In the model, as specialists' option values grow, the optimal contract prescribes an increase in their compensation as a form of retention. Intuitively, because contract termination is costly to investors, raising specialists' compensation level is consistent with lowering the likelihood of termination. This positive correlation across outside options and compensation arises endogenously from the optimal contract despite the independence of shocks across (3.3) and (3.5).[16]

[16]This result is not inconsistent with the findings of our empirical regressions or the targets of the indirect inference in our internal calibration. In these regressions, we include firm fixed effects. In the model when regressing turnover on outside options, the fixed effect holds w fixed and the regressor varies $w(a)$. Conditional on compensation w, raising a will increase the likelihood of leaving. In the quintiles, by contrast, w reflects equilibrium forces that pushes it towards $\overline{w}(a)$, the part of the state space where agency frictions and the probability of turnover are minimized.

In the third row we tabulate the annual probability of turnover. We count the instances of contract termination in the empirical and simulated data and convert them to a frequency. As the values of outside options rise, this probability falls, reflecting investors' effort at retaining specialists by paying them more.

Investment Decomposition

In the fourth row of each panel in Table 3.5, we compare the effects of outside options on intangible investment. To isolate the effect of outside options on investment we control for compensation. In the model, this is like holding stake w fixed while we vary skill a. Investment net of compensation is the residual from a regression of intangible investment rates on compensation. Investment rates decline with specialists' value of outside options in both model and data. Once controlling for compensation, they are positive at low quintiles but become negative at high quintiles.

We use the model to gain insight on these investment patterns by decomposing it in the bottom three rows of Panel B via the marginal benefit of investment in (3.22). First, the average gain to investors per unit of intangible capital, $p(a,w)$, falls. Specialists with large outside options effectively possess a great share of inside equity and thus the return for investors has been reduced. In effect, a greater fraction of the rewards to intangible capital are earned by specialists, not owners.

Second, agency's impact on investment, similar to DeMarzo et al.'s (2012), is reported in the second-to-last row. Investment reduces the effective share that specialists have in the firm as $w = W/N$ declines in N. This exacerbates the agency friction and results in lower investment. We see that the magnitude of this effect becomes pronounced when specialists have a valuable outside option. The risk of appropriation thus magnifies the agency conflict's adverse effect on investment.

Third and last, appropriation lowers the marginal benefit to investment. Intuitively, investment raises agents' skill and their likelihood of leaving, which impacts the probability of costly termination. This effect is captured in the right-most term of (3.22), $\kappa p_a(w,a)a$, which is negative. In addition, the set of firms near the termination boundary are also likely to face retention costs, as captured in (3.23). Both retention costs and appropriation serve to lower the expected return on capital. This appropriation cost has about one-third to one-half of the impact that agency costs alone have on lowering investment.

Dynamic Contracting Implications

Recall that Section 3.3.4 shows our model has history dependence. In particular, specialists' total compensation depends on the history of agents' skill a. Following Ai et al. (2021) we proxy for this history by looking at changes in the running maximum of the value of specialists' outside options. Specifically, we calculate $\max \gamma w(a_t) = \sup_{0 \leq s \leq t} \gamma w(a_s)$ for each time t, and compute the three-year change in this running maximum.

We look at whether three-year differences in this maximum, once controlling for compensation, are informative about changes the severity of the agency conflict. Intuitively, all else equal, a recent growth in the value of outside options would exacerbate the severity of the agency conflict, lowering the expected return on investment and also increasing the likelihood that the specialist leaves. Thus we expect the coefficient on the three-year change to be negative for investment and positive for turnover. In Table 3.6, we test this prediction by regressing turnover and investment on compensation and the three-year change. The signs of these coefficients are consistent with this intuition.

Altogether, these dynamic contracting implications of the model are supported empirically. This confirms the model's ability in replicating the key features of the data.

3.6 Counterfactual Analysis on Worker Mobility

Having verified the model's ability to match the data, in this section we use the model to run counterfactuals. We use steady state analysis (Hopenhayn (1992)) to see how a change in model parameter impacts the stationary density of firms and their policy functions. Here, we are interested in how the distribution of investment rates vary in response to the appropriation parameter, κ. We use this to analyze whether growth rates could possibly be increased by tightening or easing constraints on the ability of specialists to appropriate knowledge. Though the stationary distributions remain constant conditional on a choice of κ, they do so only by the offsetting effects of firm expansion and contraction, of specialist departure and re-employment. Steady state analysis is thus suited to understanding the long-run effects of these changes.

We summarize our steady state analysis with Figure 3.6. The model produces a hump-shaped pattern that reflects the tension between competing interests. On the one hand, strict enforcement of appropriability (low values of κ) are too burdensome on employees. As a result, it is harder to motivate specialists and providing them incentive to work becomes costly. This is a world of severe agency conflicts. On the other hand, lax enforcement (high κ) reduces the ability of the firm's owners to capture the rents associated with intangible investment (Arrow, 1962). Investment is thus pared, as is the value that accrues to investors and managers.

The graph finds the maximum value to be attained at $\kappa = 0.3$, a value 0.1 units smaller than the current estimate. The economy's growth rate could be raised by approximately 10 basis points a year from a modest tightening of restrictions on labor mobility. This prediction is consistent with our empirical results of Section 3.4 and, in the language of Arrow (1962), owners' concerns modestly taking precedence over employees'.

How do we map κ to the data? In the data, we exploit variation in an ordinal variable, *NCEI*, which does not measure directly the appropriation parameter. Instead, we link both model and data through the variation in the scaled value of outside options observed when changing either *NCEI* by one unit or κ by an appropriate amount. Thus, outside options are the key to bridging model and data.

Empirically, column (4) of our first-stage regression in Table 3.1 shows that a unit increase in *NCEI* leads to a 0.005 reduction in the value of an executive's outside option per unit of intangible capital. By way of simulation, we estimate that the required decline in κ in the model to generate the same reduction in the scaled outside option value is 0.1. Hence, the model predicts that to increase investment the non-compete enforcement index should grow by approximately one unit on average across all states.

We should be cautious, however, in advocating only for owners' interest. The figure shows that one should not restrict mobility too much, as the average growth rate begins to drop after more than a 0.1 reduction in κ. Thus, extrapolating local average treatment effects in conducting policy might lead to unintended consequences.

Our analysis provides a forceful critique to the sweeping proposal put forward by the FTC. Our results point towards owners' and specialists' interests being nearly adequately balanced in the US economy. Economically, there is no need to tinker. On the whole, the growth rate achieved in the model calibrated to current US data is nearly maximized.

3.6.1 What Forces Change with Appropriation in the Equilibrium Distribution?

We inspect the mechanism that a modest strengthening of restrictions has worker mobility and growth.

In Figure 3.7 we show both the marginal distribution of specialists' stake, w, and the conditional investment rates given w in the top and bottom panels, respectively. Here we see that lowering κ to 0.3 shifts the distribution. In particular, there is a greater probability mass at lower values of w, especially below $w = 0.15$. Hence, specialists' in the lower tail of the compensation distribution are expected to change from this policy.

This greater mass coincides with a higher investment rate as seen in the bottom panel, explaining our finding in the previous section. Mathematically, the upper bound on stake at smaller values of skill, $w(a \approx 0)$ has been lowered. This explains the shift in the local peak of the marginal density of w moving from 0.15 to 0.14. Investors have effectively become less averse to contract termination, flattening their value function and lowering the upper bound. As a result, the marginal return on investment has grown as the adverse effects of appropriation on investment, $\kappa p_a(\cdot)a$, have fallen. Thus, lower appropriability enhances the expected return on investment.

Conclusion

William Shockley left Bell Labs in New Jersey to eventually establish Shockley Semiconductor in California. Shockley, both brilliant and abrasive, proved to be intolerable for some of his employees. A group of eight engineers, including Gordon Moore, quit Shockley to start several ventures, including Kleiner Perkins and Fairchild Semiconductor, which led to Intel. What would our world be like today if Shockley, Moore, and others were prohibited from leaving their firms? While this sequence of events was among the most fateful, history is littered with countless examples.

We lay the foundation and take a solid step towards answering this question. We formulate a novel structural growth model that places at its fore the competing interests of investors and specialists. We then calibrate the model to a crafted empirical environment that exploits variation in a state-level enforcement index of non-compete agreements. We use our theoretical environment to study counterfactuals on how worker mobility affects growth.

We conclude that the *current* structure of employment restrictions is near growth-optimal and adequately balances stakeholders' interests. Our work emphasizes the importance of a perspective that may be being downplayed or outright ignored by the FTC when deciding how to regulate workers' mobility—the investment incentives of owners to be able to fully retain the rewards from their continued investment in intangible capital.

Table 3.1. First Stage: Enforceability on CEOs' Outside Option Values

This table reports the first-stage regression results for the effect of the enforceability of non-compete agreements on the value of CEO outside options. The variable $\log \text{Outside Option}$ is the logarithm of one plus the outside option for CEOs. The level of non-compete enforceability index is *NCEI* and changes in the index, Δ*NCEI*, are one if the firm's state's *NCEI* is higher than the 1992 initial value in a given year, negative one if it is lower than that, and zero if unchanged. Control variables are all lagged and include the investment rate, turnover, Tobin's Q, cash, profitability, leverage, the logged level of intangible capital, and a CEO indicator for whether her/his age is above 62. We include firm- and year-fixed effects. Observations are at the firm-year level. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Variable:	$\log \text{Outside Option}$	$\log \text{Outside Option}$	$\frac{\text{Outside Option}}{\text{Intangible Capital}}$	$\frac{\text{Outside Option}}{\text{Intangible Capital}}$
NCEI	−0.041***		−0.004***	
	(0.01)		(0.00)	
Δ*NCEI*		−0.053***		−0.005***
		(0.01)		(0.00)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	20,316	20,316	20,316	20,316
F-stat	49.66	60.79	23.51	23.46

Table 3.2. Second Stage: CEOs' Outside Option Values on Investment and Turnover

This table provides the second-stage regression results for the effect of shocks to outside options on intangible investment and CEO turnover. The variables $\log \widehat{\text{Outside Option}}$ and $\widehat{\text{Outside Option/Intangible}}$ Capital are the instrumented outside option index for CEOs obtained in Table 3.1. Intangible Investment Rate is the investment rate of intangible capital in a given year. R&D Investment is R&D expenditure scaled by intangible capital. CEO Turnover is one if the company has a CEO turnover and zero otherwise. Control variables are all lagged and include the investment rate, turnover, Tobin's Q, cash, profitability, leverage, the logged level of intangible capital, and a CEO indicator for whether her/his age is above 62. We include firm- and year-fixed effects. Observations are at the firm-year level. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Logged Outside Option

	Instrument: *NCEI*			Instrument: Δ*NCEI*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	Intangible Investment Rate	R&D Investment	CEO Turnover	Intangible Investment Rate	R&D Investment	CEO Turnover
$\log \widehat{\text{Outside Option}}$	−0.072*	−0.169***	0.166*	−0.066*	−0.169***	0.219**
	(0.04)	(0.06)	(0.10)	(0.03)	(0.06)	(0.11)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	20,316	20,316	20,316	20,316	20,316	20,316

Panel B: Outside Option over Intangible Capital

	Instrument: *NCEI*			Instrument: Δ*NCEI*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	Intangible Investment Rate	R&D Investment	CEO Turnover	Intangible Investment Rate	R&D Investment	CEO Turnover
$\frac{\widehat{\text{Outside Option}}}{\text{Intangible Capital}}$	−0.711*	−1.685***	1.652	−0.705*	−1.799**	2.333*
	(0.39)	(0.65)	(1.03)	(0.38)	(0.70)	(1.24)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	20,316	20,316	20,316	20,316	20,316	20,316

Table 3.3. High-Skilled Employees' Outside Option Values on Firm Investment

This table shows both first- and second-stage regression results for the effect of shocks to high-skilled employees' outside options on firms' intangible investment. The variable $\log \widehat{\text{Outside Option}}_{HS}$ is the instrumented outside option index for workers in high-skilled industries. Intangible Investment Rate is the investment rate of intangible capital in a given year. R&D Investment is R&D expenditures scaled by intangible capital. Control variables are all lagged and include the investment rate, turnover, Tobin's Q, cash, profitability, leverage, and the logged level of intangible capital. We include firm- and year-fixed effects. Observations are at the firm-year level. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Instrument: *NCEI*			Instrument: Δ*NCEI*		
	First stage	Second stage		First stage	Second stage	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	$\log$ Outside Option$_{HS}$	Intangible Investment Rate	R&D Investment	$\log$ Outside Option$_{HS}$	Intangible Investment Rate	R&D Investment
NCEI	−0.023***					
	(0.00)					
Δ*NCEI*				−0.022***		
				(0.00)		
$\log \widehat{\text{Outside Option}}_{HS}$		−0.061	−0.352***		−0.081	−0.419***
		(0.07)	(0.12)		(0.09)	(0.15)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	13,306	13,306	13,306	13,306	13,306	13,306
F-stat	93.14			51.31		

Table 3.4. Summary of Calibration (Annual)

This table summarizes the chosen values of the benchmark calibration discussed in Section 3.5

Panel A: External Parameters		
Description	Value	
Real interest rate, r	0.04	
Intangible depreciation rate, δ_N	0.15	
Capital doubling time, θ	20	
Loss given turnover, l	0.94	
Volatility of intangible capital growth, σ_N	0.20	
Fraction of good matches, ζ	0.30	
Specialists' relative bargaining power, ψ	0.50	
Panel B: Internal Parameters		
Description	Value	
Average investment growth, z	0.028	
Specialists' discount rate, γ	0.100	
Agency friction, λ	0.290	
Productivity, Z	0.224	
Variation in skill, σ_a	0.035	
Appropriability, κ	0.400	
Panel C: Targeted Moments		
Moment/regression coefficient	Model	Data
Average compensation	0.013	0.018
Average turnover rate	0.051	0.047
Average profitability	0.022	0.042
Average investment rate	0.197	0.212
Turnover on scaled outside option	3.416	2.333
Investment rate on scaled outside option	−2.150	−0.705

Table 3.5. Characteristics of Outside Option Quintiles and Investment Decomposition

This table lists time-series averages of characteristics of quintiles annually on firms' outside option-to-intangible capital ratio in both data and model. In the model, we use our simulated data from model's steady state. Outside option is $\underline{w} = \underline{W}/N$, agent's compensation is $\gamma w = \gamma W/N$, the probability of turnover is annualized average exit rate: $P\{w_{t+1} < \underline{w}(a_t)\}$, and the investment rate is g. In both the model and data, investment net of compensation is calculated as the residuals of regressing investment on compensation.

Panel A: Data					
	Outside Option Quintile				
	1	2	3	4	5
Outside option	0.00003	0.0002	0.0006	0.0017	0.0091
Compensation	0.0090	0.0072	0.0124	0.0193	0.0371
P(turnover)	0.040	0.045	0.042	0.041	0.029
Investment net of compensation	0.0004	0.0021	0.0005	−0.0019	−0.0018
Panel B: Model					
	Outside Option Quintile				
	1	2	3	4	5
Outside option	0.0004	0.0008	0.0013	0.0021	0.0054
Compensation	0.0124	0.0127	0.0130	0.0135	0.0155
P(turnover)	0.0525	0.0547	0.0530	0.0492	0.0461
Investment net of compensation	0.0023	0.0008	0.0001	−0.0011	−0.0039
Investment decomposition: $c'(g) = p(a,w) - p_w(a,w)w + \kappa p_a(a,w)a$					
Investor value, $p(a,w)$	1.583	1.411	1.218	1.054	0.950
Agency cost, $p_w(a,w)w$	0.038	−0.022	−0.091	−0.130	−0.133
Appropriation cost, $\kappa p_a(a,w)a$	−0.030	−0.062	−0.084	−0.076	−0.056

Table 3.6. Implications of dynamic contracting

This table presents estimates of panel regression coefficients in both data and model. All data regressions exclude 2008 and 2009 and control for firm- and year-fixed effects $y_{it} = f_i + f_t + \alpha_i C_{it-1} + \beta_i X_{it-1} + \epsilon_{it}$, where C_{it-1} is our set of lagged controls listed in Appendix. Investment is the investment rate of intangible capital. In the data, we calculate $\gamma w(a_{it-1})$ using the ratio of outside option values (3.24) to firm's intangible capital (3.27). All model regressions are done in the stationary distribution and control for firm-fixed effects: $y_{it} = f_i + \beta_i X_{it-1} + \epsilon_{it}$, where $X_{it-1} = \max \gamma w(a_{it-1}) = \sup_{0 \leq s \leq t-1} \gamma w(a_{is})$. The table lists the coefficient estimates of turnover or the intangible investment rate, g, regressed on compensation, γw, and a three-year difference of the running maximum, $\Delta_3 \max \gamma w(a_{it-1}) = \max \gamma w(a_{it-1}) - \max \gamma w(a_{it-4})$, where $\max \gamma w(a_{it-1}) = \sup_{0 \leq s \leq t-1} \gamma w(a_{is})$ in the model. Standard errors are in parentheses.

Three-year Change in Running Maximum				
	Turnover		Investment	
	Model	Data	Model	Data
Compensation	−29.492	−0.116	1.896	0.136
	(1.167)	(0.113)	(0.051)	(0.082)
$\Delta_3 \max w(a_{it-1})$	9.458	0.150	−2.031	−0.137
	(4.647)	(0.099)	(0.386)	(0.090)

Figure 3.1. Illustration of Agency, Appropriation, and Bargaining Power

This figure illustrates how specialists' skill of appropriation and bargaining power affect the solution to investors' problem. Figures in the left panel plot the investor's value function $p(w)$ and investment rate $g(w)$ when the agency cost is low, $\lambda = 0.7$, and figures in the right panel plot the investor's value function and investment rate when the agency cost is high, $\lambda = 1.3$. In each figure there are three cases: (1) no skill of appropriation: $a = 0$, (2) positive skill of appropriation and investor power, (3) positive skill of appropriation and specialist power. The other parameters are $r = 0.04$, $\gamma = 0.045$, $\theta = 30$, $\delta_N = 0.1$, $Z = 0.16$, $\sigma_N = 0.35$, and $l = 0.8$.

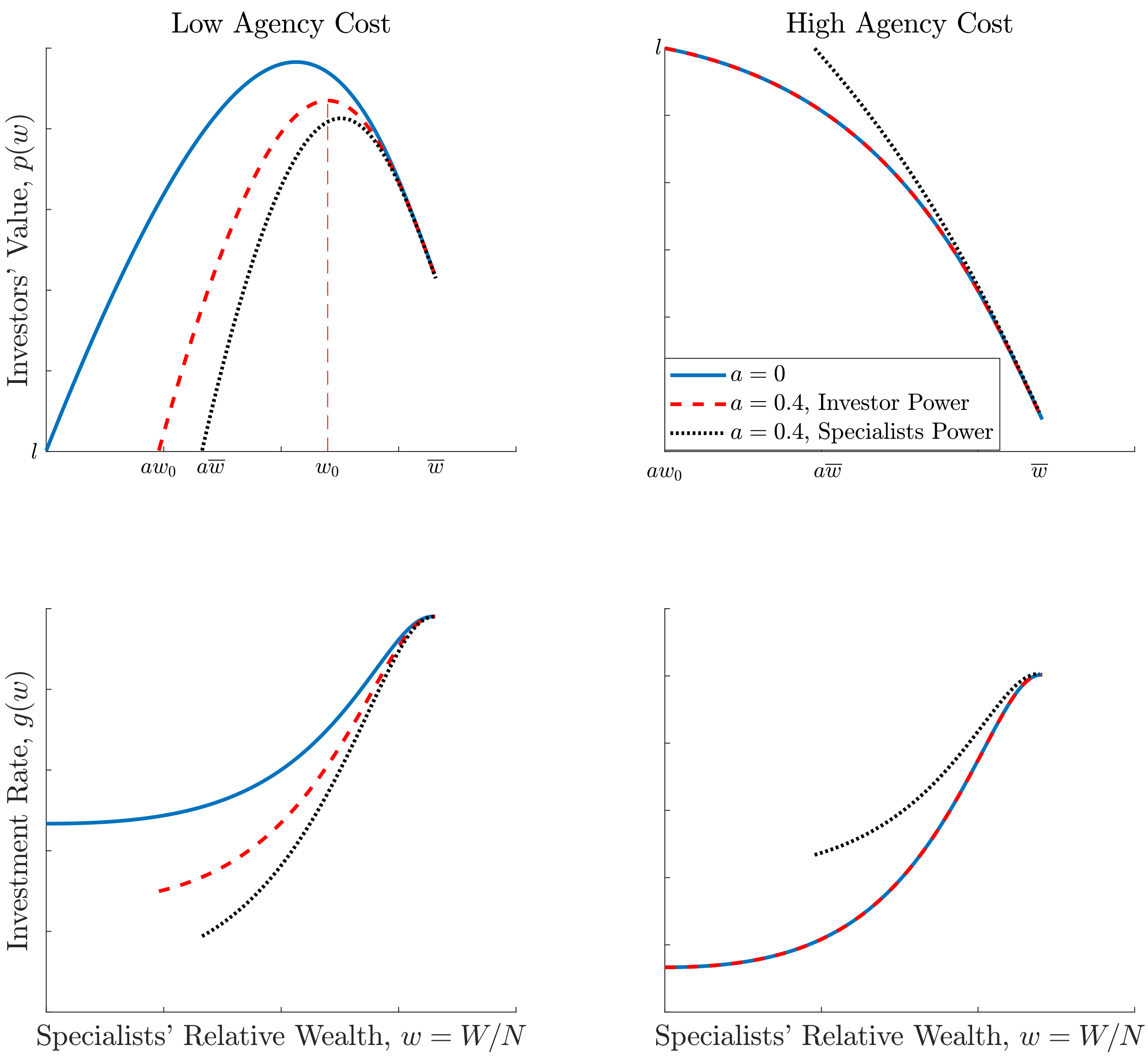


Figure 3.2. Distribution of NCEI

This figure shows the distribution of the values of the non-compete enforceability index (NCEI) across our state-year sample. Higher values indicate stricter enforcement of non-compete agreements.

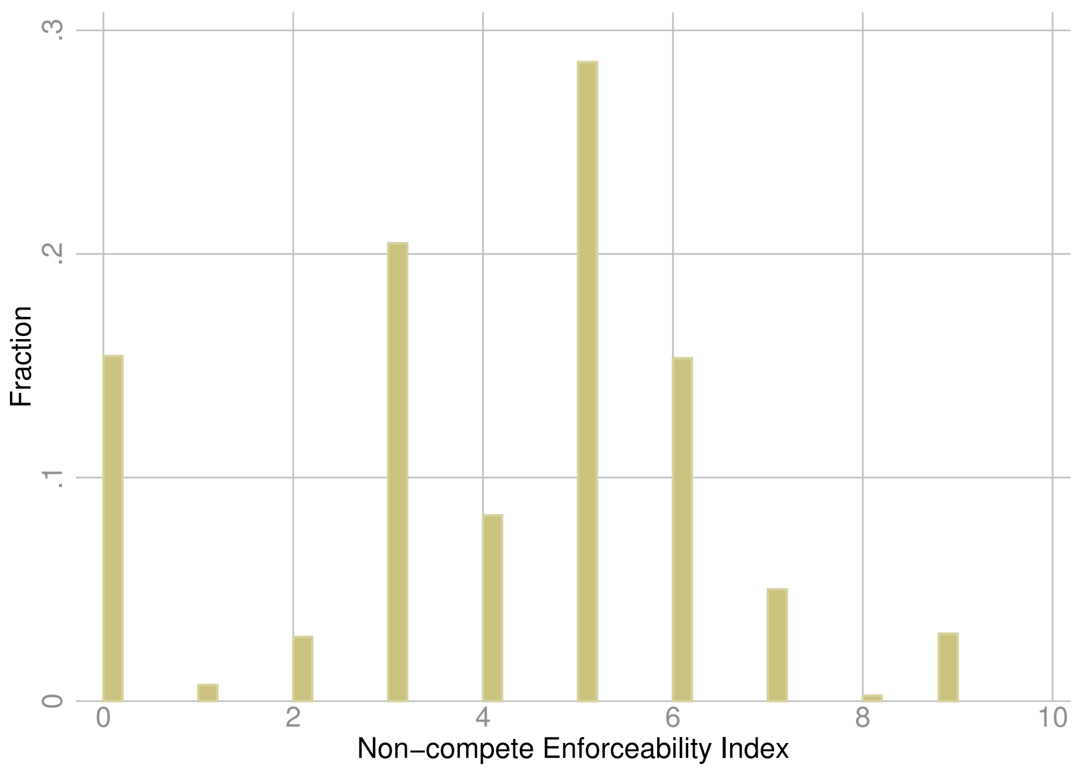
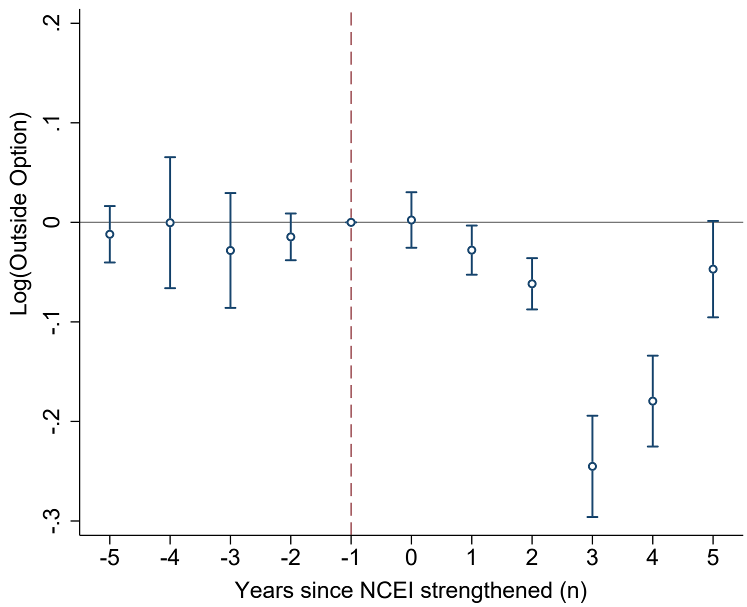


Figure 3.3. Parallel Trends: NCEI Changes on Outside Options

This figure provides parallel trends for the first-stage regressions, the effect of strengthening of the NCEI ($\Delta NCEI > 0$) on the outside option (log(Outside Option)). Each data point represents the point estimate of the interaction of time dummies with $\Delta NCEI$. The control groups are constructed following the methodology of Sun and Abraham (2021): the top figure uses firms that are never treated as the control group, while the bottom figure uses firms that were last treated as the control group. Bars represent 95% confidence intervals based on errors clustered at the firm-level.

(a) Control Group: Never Treated



(b) Control Group: Last Treated

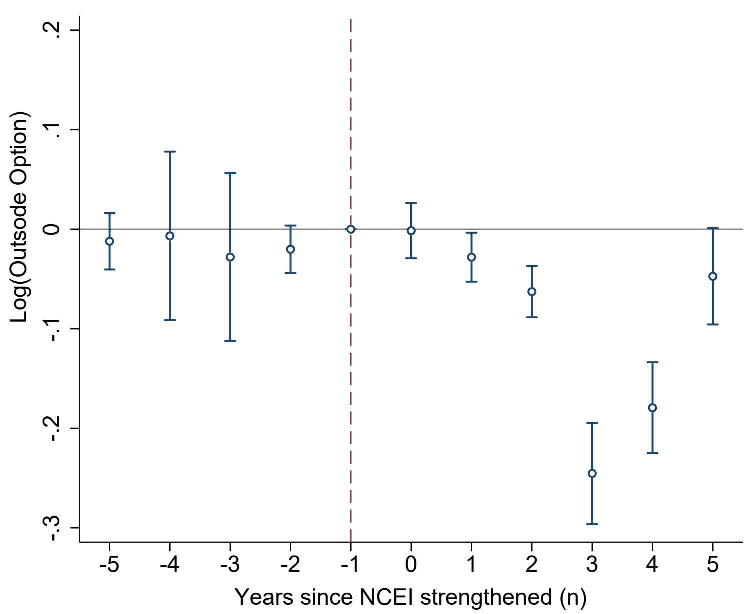


Figure 3.4. Value Function

This figure plots top-down investors' scaled value $p(a,w) = P(a,N,W)/N$ as a function of specialists' skill a and stake $w = W/N$ (their scaled continuation payoff). A brighter color denotes a higher value. The dotted line depicts ${}_w p(a,w)$ for each a. The dashed line represents $a\overline{w}(a)$.

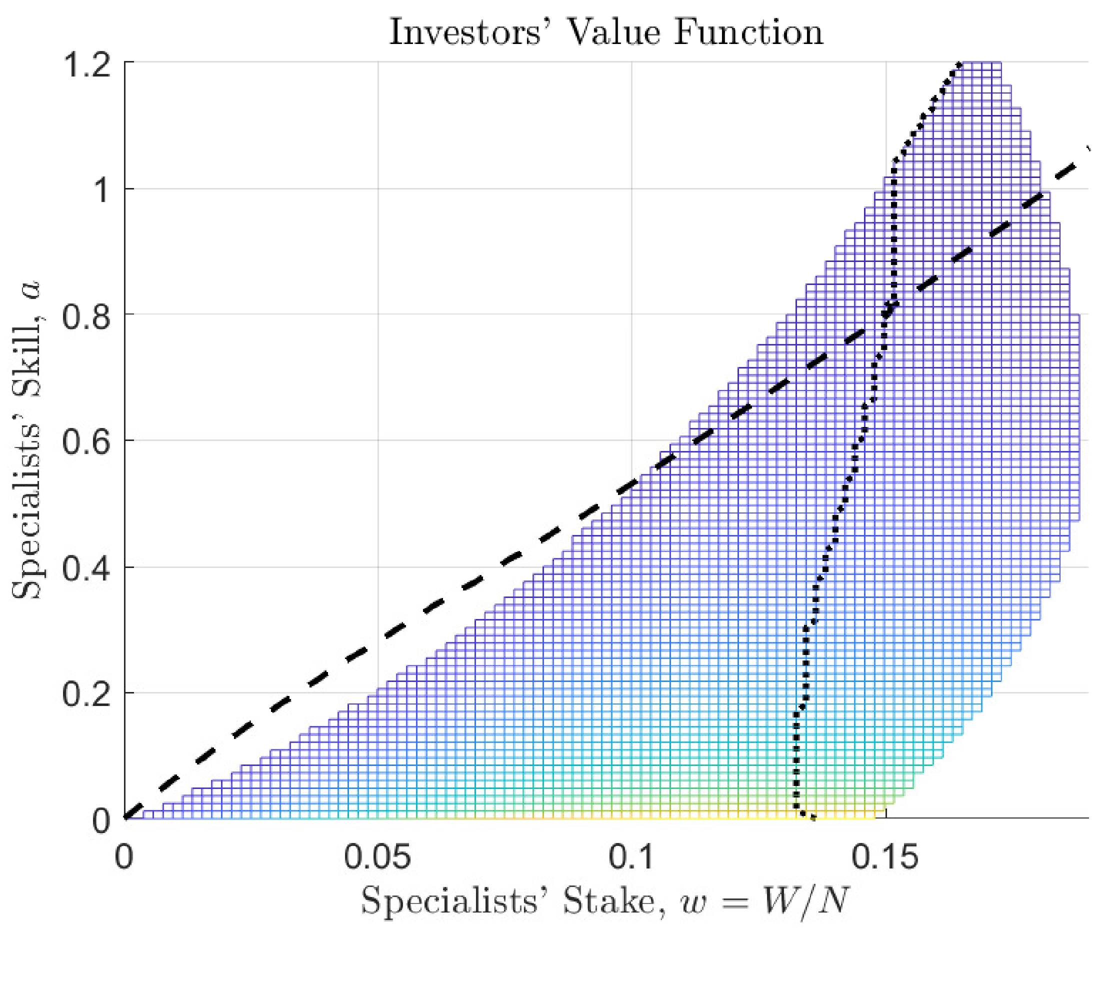


Figure 3.5. Comparison of Distribution of Outside Options

This figure plots the density distribution of specialists' outside options in model and data (for CEOs). The data's outside option value is scaled by intangible capital and has a correction for a CEO's probability of finding a job conditional on leaving one. The outside option in the model is $\gamma \underline{w}$.

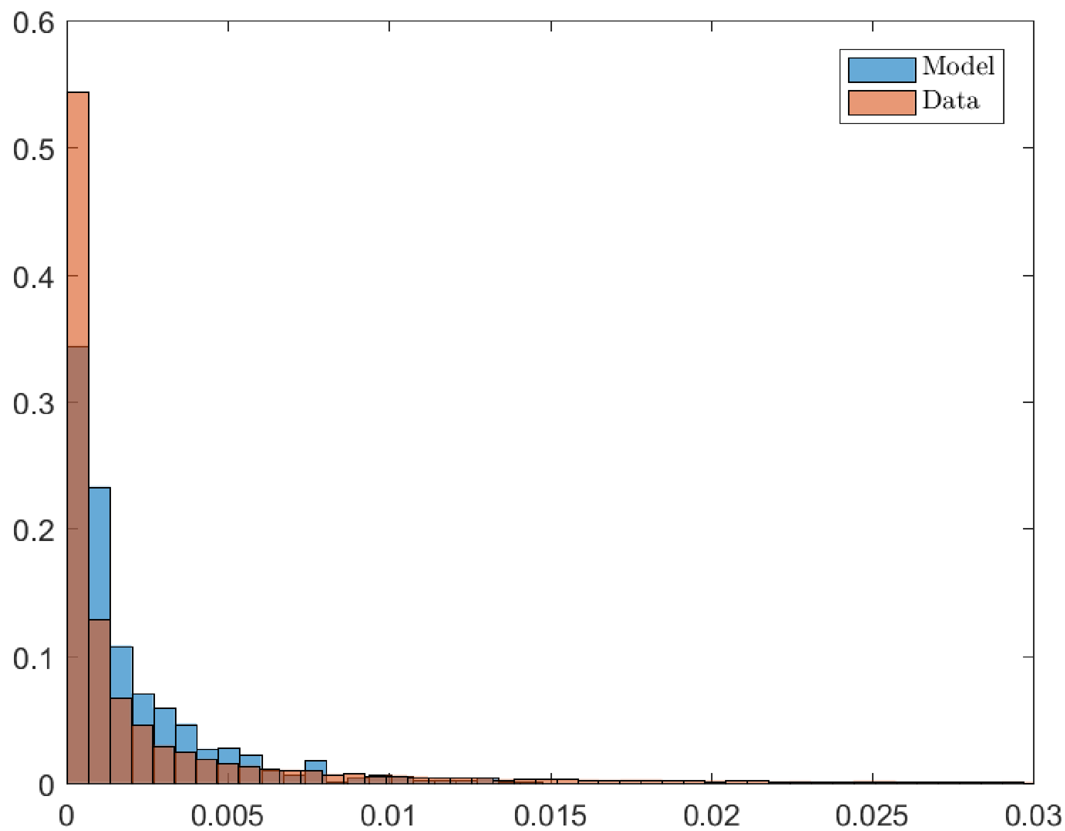


Figure 3.6. Counterfactual Analysis on Appropriability

This figure depicts the average intangible investment rate, investor value, specialist value, and their total value as a function of appropriability using simulated data from the model. They are computed as the time series average of mean investment rate g, mean investor value p, mean specialist value w, and mean combined $(p+w)$ value across firms, respectively. Our current estimate is denoted by the vertical dashed red line.

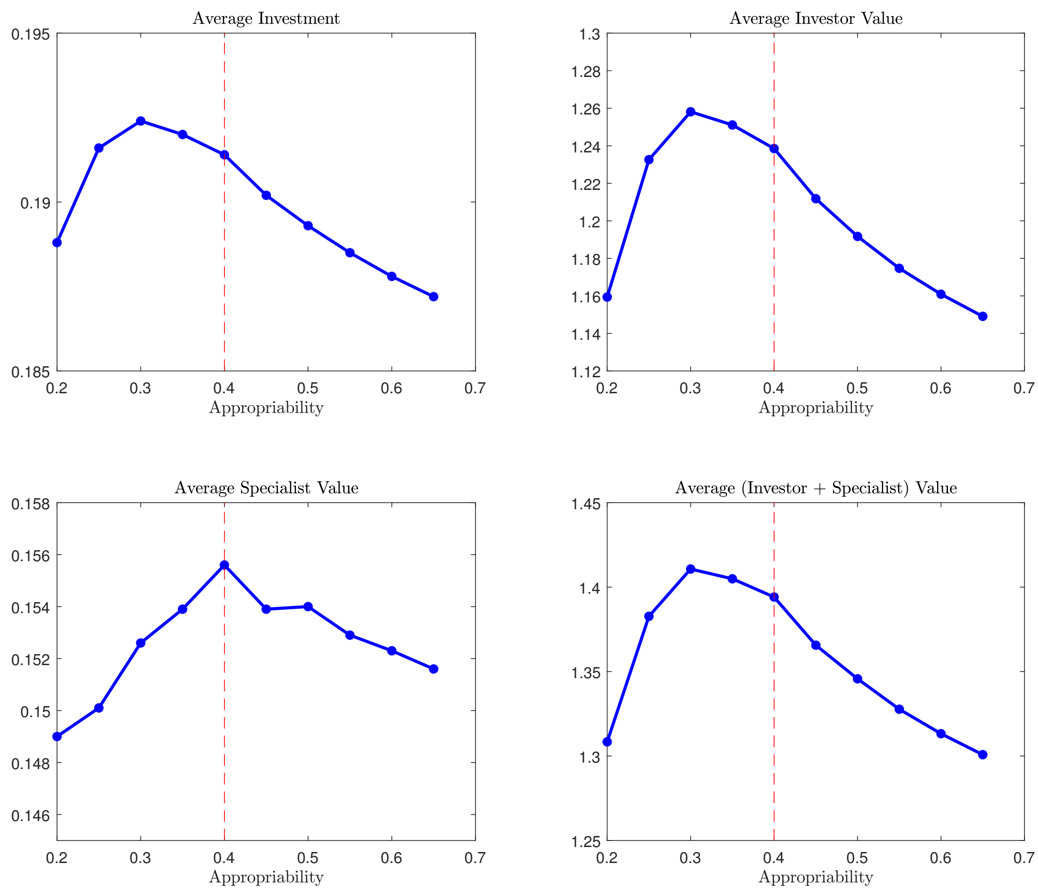
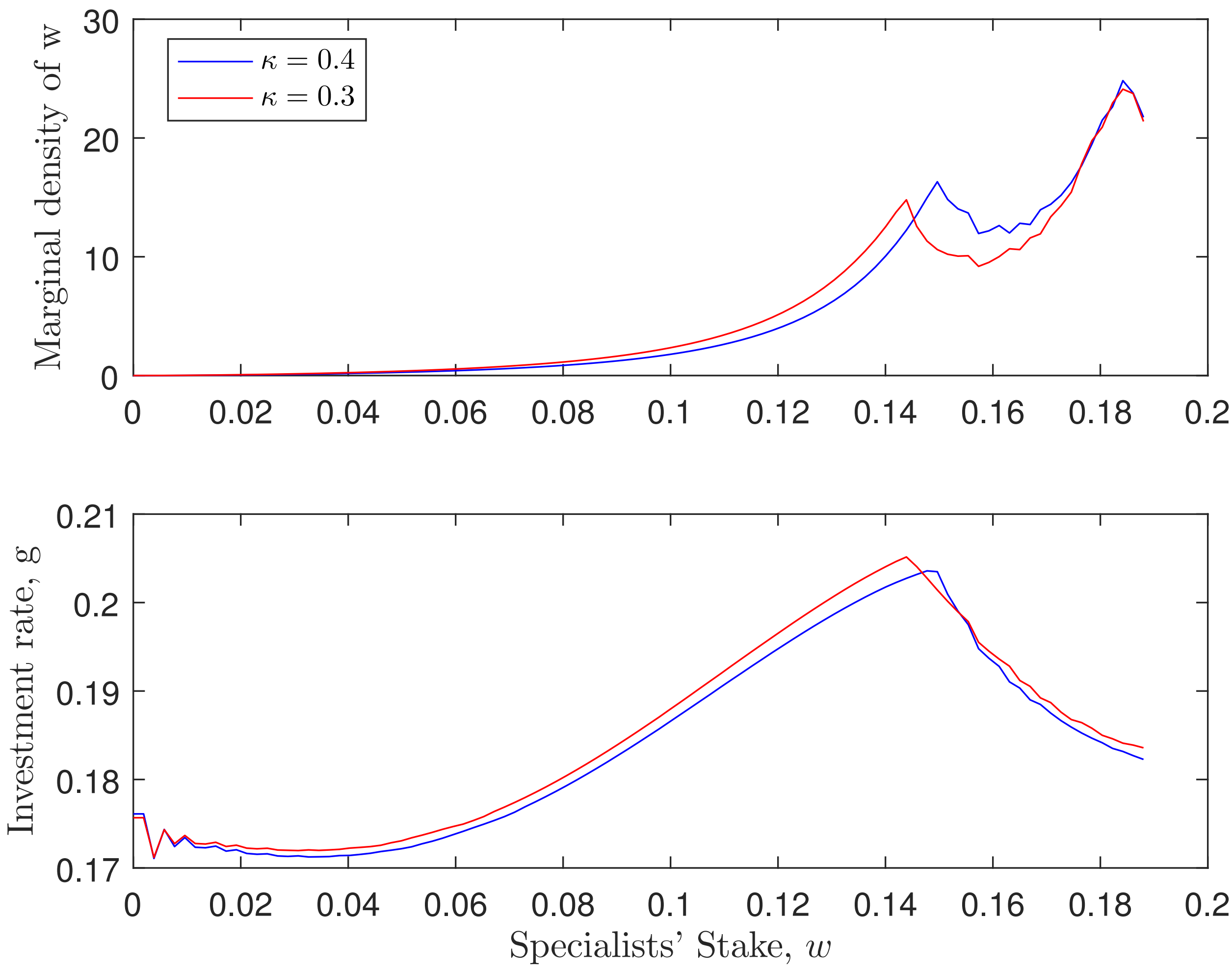


Figure 3.7. Decomposition of Average Investment

The top panel depicts the marginal density of specialists' stake, w, for two values of appropriability κ. The bottom panel shows the conditional investment rate as a function of w for each value of appropriability.



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Appendix A

Chapter One Appendix

A.1 Details on Data Construction

A.1.1 Monetary Shocks

I use the daily measures of monetary policy shocks from Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016) (hereafter, GSS and GW) as the baseline measures in the main analysis, and the measures from Nakamura and Steinsson (2018) and Gertler and Karadi (2015) in the robustness test.

GSS and GW measure monetary shocks as the changes in the current month's federal fund futures rate in a 30-minute narrow window around the FOMC announcement. I exclude unscheduled meetings and conference calls, which helps to mitigate the problem that monetary surprises may contain private central bank information about the state of the economy (Reinelt and Meier (2020)). I further exclude the apex of the financial crisis from 2008Q3 to 2009Q2. The sample runs from 1990 to 2018. Gertler and Karadi (2015) use federal funds futures three months ahead to measure daily monetary shocks (FF4), and the sample runs from 1990 to 2012. I also use the policy news shock from Nakamura and Steinsson (2018) as a robustness check. The sample runs from 1995 to 2018.

I follow Ottonello and Winberry (2020) to aggregate the shocks to the quarterly frequency. I assign daily shocks fully to the current quarter if they occur on the first day of the quarter. If they occur within the quarter, I partially assign the shock to the subsequent quarter. This procedure weighs shocks across quarters corresponding to the amount of time agents have to respond.

Results based on Nakamura and Steinsson (2018)'s policy news shock can be found in Tables A.9.

A.1.2 Aggregate Variables

The aggregate variables used in the empirical test include nonfinancial corporate debt (debt securities and loans) from flow of funds and other variables such as price deflator (IPD: Nonfarm business sector: implicit price deflator), real GDP growth (GDPC1: Real Gross Domestic Product), the inflation rate (CPIAUCSL: Consumer Price Index for All Urban Consumers: All Items), the unemployment rate (UNRATE: Unemployment Rate), credit spread (the spread between BAA and AAA), term spread (the spread between 10-year Treasury rate and 1-year Treasury rate), loans and leases (TOTLL: Loans and Leases in Bank Credit, All Commercial Banks), commercial paper (CPLBSNNCB: Nonfinancial Corporate Business; Commercial Paper), commercial & industrial loans (TOTCI: Commercial and Industrial Loans, All Commercial Banks) and real estate loans (RELACBW027SBOG: Real Estate Loans, All Commercial Banks) available from the

Federal Reserve Bank of St. Louis, as well as the Greenbook forecasts and forecast revisions available from the Federal Reserve Bank of Philadelphia. The price-dividend ratio (PD) is obtained from Shiller's website, and intermediary financial leverage (HKM) is obtained from Asaf Manela's website. Interest rate swaps and LIBOR are available on Bloomberg.

A.1.3 Firm Variables

Debt Data

New loan issuance data are obtained from DealScan, and new bond issuance data are obtained from FISD. I obtain the firm-level loan share from Compustat. A limitation of Compustat's balance sheets is that they do not report loans separately from the rest of the outstanding debt. Following Crouzet (2021), I approximate the firm-level loan share using the sum of two variables: a short-term debt variable, notes payable (NP), and long-term debt variables, other long-term debt (DLTO). The advantage of this definition is that it provides a comprehensive long-run measure of the loan share at the firm level.[1] For short-term debt, NP includes bank acceptances, bank overdrafts, and loans payable. For long-term debt, DLTO includes all revolving credit agreements, as well as all construction and equipment loans. It excludes senior nonconvertible bonds (which are included in debentures, DD) and convertible or subordinate bonds (included in DCVT and DS, respectively). The main drawback is that both NP and DLTO include outstanding commercial papers. Crouzet (2021) provides evidence for the fact that this measure of the loan share indeed captures the ratio of total debt outstanding. Since other long-term debt (DLTO) is not available at the quarterly frequency, I construct it as: $\text{DLTOQ}_{i,t} = \frac{\text{DLTO}_{i,\tau(t)}}{\text{DLTT}_{i,\tau(t)}}\text{DLTTQ}_{i,t}$ or zero if $\text{DLTT}_{i,\tau(t)} = 0$, where $\text{DLTO}_{i,\tau(t)}$ and $\text{DLTT}_{i,\tau(t)}$ are the balance sheet values from the firm's annual report at the annual reporting date $\tau(t)$ that immediately precedes quarter t.

Equity Data

Firm-level net equity issuance is defined as the sale of common and preferred stock minus the purchase of common and preferred stock, scaled by the lagged total asset. Equity issuances are all funds received from the issuance of common and preferred stock. They include the exercise of stock options or warrants for employee compensation. Therefore, this measure may overstate equity issuances for financing reasons. I address this concern following McKeon (2015) by considering only equity issuances that are larger than 2% of end-of-quarter market equity, defined as PRCCQ $\times$ CSHOQ.

Firm-level equity stock is measured as the difference between the total asset (ATQ) and total debt (DLTTQ + DLCQ). The change in equity share every period is therefore changed in equity stock, scaled by the lagged total asset.

Distance to Default

Following Merton (1974) and Gilchrist and Zakrajšek (2012), the distance to default is defined as

$$D2D = \frac{log(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}, \tag{A1}$$

where V is the total value of a firm, μ_V is the annual expected return on V, σ_V is the annual volatility of the firm's value, and D is the firm's debt. Firm value V is estimated following an iterative procedure:

1. Set an initial value for the firm value equal to the sum of firm debt and equity: $V = E + D$, where $E = \text{PRC} \times \text{SHROUT}$ (daily stock price times the number of shares outstanding from CRSP).

[1] Notes payable are not reported as a separate item before 1970Q1.

2. Estimate μ_V and σ_V over a 250-day moving window. The return on firm value is defined as the daily log return on assets, $\Delta logV$.
3. Get a new estimate of V for every day of the 250-day moving window based on the Black-Scholes-Merton option-pricing framework

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2) \tag{A2}$$

, where $\delta_1 = \frac{log(V/D)+(r+0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}}$ and $\delta_2 = \delta_1 - \sigma_V\sqrt{T}$ where r is the daily one-year constant maturity Treasury yield from the St. Louis Fed.
4. Iterate on steps 2 and 3 until convergence.

Measures of Financial Constraints

Existing proxies aim to infer financial constraints from firms' statements about their funding situation, their actions (such as not paying a dividend), or their characteristics (such as being young or small, having low leverage, or having no credit rating). I use the Whited-Wu index (WW), Size & Age index (SA), firm size, credit rating, and distance to default as proxies for financial constraints. The SA index is constructed following Hadlock and Pierce (2010) as $\text{SA Index} = -0.737\text{Size} + 0.043\text{Size}^2 - 0.040\text{Age}$. The WW index is constructed following Whited and Wu (2006a) and Hennessy and Whited (2007) as $\text{WW Index} = -0.091\text{CF} - 0.062\text{DIVPOS} + 0.021\text{TLTD} - 0.044\text{LNTA} + 0.102\text{ISG} - 0.035\text{SG}$.[2] Firms are sorted into terciles based on their index values in the previous period. Firms in the top tercile are coded as constrained, and those in the bottom tercile are coded as unconstrained. The definition and source of all variables are shown in Table A.1.

Sectoral dummies

1. Agriculture, forestry, and fishing: SIC < 999;
2. Mining: SIC $\in$ [1000, 1499];
3. Construction: SIC $\in$ [1500, 1799];
4. Manufacturing: SIC $\in$ [2000, 3999];
5. Transportation, communications, electric, gas, and sanitary services: SIC $\in$ [4000, 4999];
6. Wholesale trade: SIC $\in$ [5000, 5199];
7. Retail trade: SIC $\in$ [5200, 5999];
8. Services: SIC $\in$ [7000, 8999].

A.1.4 Bank Variables

Bank holding company balance sheet variables are obtained from FR Y-9C.

Bank size is defined as the log of total assets (BHCK2170), and the capital ratio is defined as the ratio of Tier 1 capital (BHCK3210) to total assets. Return of equity is the ratio of net income (BHCK4340) to bank capital (BHCK3210). Total deposits are given by (BHDM6631 + BHDM6636 + BHFN6631 + BHFN6636), and cost of funding is measured as interest expense (BHCK4073)/(total deposit + other borrowing (BHCK3190)). Total non-performing loans are given by
(BHCK5524+BHCK5525+BHCK5526+BHCK4635), while total loans are the sum of BHCK2122 and BHCK2123. The non-performing loan share is calculated as total non-performing loans divided by total loans.

[2] CF is cash flow to total assets, DIVPOS is a dummy for positive dividend payout, TLTD is long-term debt to total assets, LNTA is logarithm of total assets, ISG is firm's three-digit industry sales growth, and SG is firm-level sales growth.

A.1.5 Sample Construction

Compustat

I apply the following filters to my Compustat sample:

- I drop firms in finance, insurance, and real estate sectors (SIC ∈ [6000, 6799]), utilities (SIC ∈ [4900, 4999]), non-operating establishments (SIC = 9995), and industrial conglomerates (SIC = 9997);
- I drop firms not incorporated in the United States;
- I drop observations with negative or missing sales or assets;
- I drop observations with negative liquidity, short-term/long-term debt, property, plant, and equipment (negative CHEQ, DLCQ, DLTTQ, and PPENTQ);
- I drop observations with missing acquisitions or quarterly acquisitions (AQCY) that are greater than 5% of total assets;
- I drop firms with observations less than three years in the final sample (1990-2018).

DealScan

Loan Issuance

I apply the following filters to my DealScan sample:

- I keep facilities measured in U.S. dollars;
- I keep facilities with borrowers and lenders in the USA;
- I keep facilities using "LIBOR" as the base rate;
- I keep facilities with loan types in the following categories: "364-Day Facility," "Revolver/Line < 1 Yr," "Revolver/Line >= 1 Yr," "Revolver/Term Loan," "Limited Line," "Term Loan (A-H)," and "Delay Draw Term Loan," which accounts for 96.7% of the whole sample;
- I keep facilities that are senior;
- I keep facilities that are distributed as "Syndication" or "Sole Lender";
- I drop facilities with negative or missing "All-in-Drawn."

Lead Agent

Syndicated loans are usually associated with multiple lenders. To determine the lead lender for each facility, I use the text variable "LenderRole" that defines the lender role and a Yes/No lead arranger credit variable "LeadArrangerCredit." I further follow Chakraborty et al. (2018) to rank the lenders:

1. LenderRole == "Admin Agent";
2. LenderRole == "Lead Bank";
3. LenderRole == "Lead Arranger";
4. LenderRole == "Mandated Lead Arranger";
5. LenderRole == "Mandated Arranger";
6. LenderRole == "Arranger" or "Agent" and LeadArrangerCredit == "Yes".

For a given loan package, the lender with the highest ranking is considered the lead agent. About 97.6% of the matched facilities in our merged sample have only one lead lender. Any loan for which a single lead agent cannot be determined is excluded from the sample.

FISD

I apply the following filters to my FISD sample:[3]

[3] I apply the same filters following Boyarchenko et al. (2022). I merge FISD and Compustat by issuers' CUSIP and TICKER. I thank Nina Boyarchenko for sharing her knowledge of bond data.

- I drop new issuance with maturity over 40 years;
- I drop new issuance with missing offering date, maturity, or offering amount, new issuance with maturity date earlier than offering date, and new issuance with offering date later than the current date;
- I drop non-corporate bond issues by "BOND_TYPE";
- I drop new issuance with zero offering amount or offering price;
- I keep new issuance from the U..S issuers (COUNTRY_DOMICILE=="USA");
- I drop Canadian, Yankee, and foreign currency bonds (FOREIGN_CURRENCY=="Y"; YANKEE=="Y"; CANADIAN=="Y");
- I keep non-convertible, non-exchangeable, and non-perpetual bonds only (CONVERTIBLE=="N"; EXCHANGEABLE=="N"; PERPETUAL=="N").

Primary market issuances are priced as a spread to nearest maturity on-the-run interest rate swaps. In particular, I use the following maturity matches in computing the offering spread:

- For bonds with a less than 4.5-month maturity, spread to the 3-month LIBOR;
- For bonds with a maturity of 4.5 months or more and less than 9 months, spread to the 6-month LIBOR;
- For bonds with a maturity of 9 months or more and less than 1.5 years, spread to the 1-year swap rate;
- For bonds with a maturity of [1.5, 2.5) years, spread to the 2-year swap rate;
- For bonds with a maturity of [2.5, 3.5) years, spread to the 3-year swap rate;
- For bonds with a maturity of [3.5, 4.5) years, spread to the 4-year swap rate;
- For bonds with a maturity of [4, 6) years, spread to the 5-year swap rate;
- For bonds with a maturity of [6, 8.5) years, spread to the 7-year swap rate;
- For bonds with a maturity of [8.5, 20) years, spread to the 10-year swap rate;
- For bonds with a maturity of [20, 30) years, spread to the 20-year swap rate;
- For bonds with 30 years maturity or more, spread to the 30-year swap rate.

Bank Holding Company: FR Y-9C

I apply the following filters to my bank holding company (BHC) sample:

- I drop observations with missing or negative total assets (BHCK2170);
- I keep bank holding companies (RSSD9331==28);
- I drop lower-tier holding companies whose higher tier also files Y-9C (BHCK9802==2);
- I keep holding company (RSSD9048 ==500) and exclude securities broker or dealer; (RSSD9048 ==700), insurance broker or company (RSSD9048 ==550), a utility company; (RSSD9048 ==710), and other non-depository institutions (RSSD9048 ==720) but keep Goldman Sachs, Morgan Stanley, Ally, and American Express;
- I drop observations with negative interest expense.

Table A.1. Variable Definitions

Definition		Data sources
Aggregate Variables		
Monetary Shocks	Monetary shocks measured by changes in fed funds futures prices around FOMC announcements	Gürkaynak et al. (2005), Gorodnichenko and Weber (2016) Nakamura and Steinsson (2018)
Corporate Debt	Credit market instrument liabilities (real debt and securities) for nonfinancial business sector	Flow of Funds
Real GDP growth	Growth rate of real GDP	NIPA
IPD	Price deflator (Nonfarm business sector: implicit price deflator)	St. Louis Fed
LIBOR	3-Month London Interbank Offered Rate (U.S.dollar)	Bloomberg
Interest Rate Swaps	Par yields based on the term-structure of LIBOR rates	Bloomberg
Treasury Yield	3M, 1Y, 2Y, 3Y, 5Y, 7Y, 10Y, 20Y and 30Y Treasury Rate	Gürkaynak et al. (2007)
UNRATE	Unemployment rate	St. Louis Fed
INFLAT	Inflation rate, defined as the log difference of CPI	St. Louis Fed
CPI	Consumer Price Index for All Urban Consumers	St. Louis Fed
Credit Spread	Moody's Baa corporate bond yield in excess of Aaa corporate bond yield	St. Louis Fed
Term Spread	10-year Treasury rate minus 1-year Treasury rate	St. Louis Fed
PD	Price-dividend (PD) ratio	Shiller's webpage
Leverage	Intermediary financial leverage ("HKM")	Asaf Manela's website
Mortgages	Nonfinancial Corporate Business; Total Mortgages	Flow of Funds L.217(Q)
Trade Credit	Nonfinancial Corporate Business; Trade Credit	Flow of Funds L.230(Q)
CPLBSNNCB	Nonfinancial Corporate Business; Commercial Paper	St. Louis Fed
TOTCI	Commercial and Industrial Loans, All Commercial Banks	St. Louis Fed
RELACBW027SBOG	Real Estate Loans, All Commercial Banks	St. Louis Fed
Firm Characteristics		
Leverage	Total debt (DLCQ + DLTTQ) over total assets (ATQ)	Compustat
Size	log(ATQ)	Compustat
Distance to default	D2D, estimated following Merton (1974) and Gilchrist and Zakrajšek (2012)	Compustat and CRSP
MB	Market-to-book value: sum of market equity (PRC × SHOUT) and total debt over total assets	Compustat and CRSP
Sales Growth	Log-difference of real sales (SALEQ/IPD)	Compustat
Dividend Payer	A dummy that takes value one when firms pay dividend (DVPQ >0)	Compustat
Credit Rating	A dummy that takes value one when rating (SPLTICRM) is above BBB^-	Compustat
Liquidity	Liquid assets (CHEQ) over total assets (ATQ)	Compustat
Trade Credit	Accounts Receivable (RECCH) over sales (SALEQ)	Compustat
Bond Characteristics		
Offering Yield	Yield to maturity at the time of issuance, based on the coupon and any discount or premium to par value at the time of sale. Offering yield is calculated only for fixed rate issues.	Mergent FISD
Offering Spread	Offering yield minus maturity-matched interest rate swaps	Mergent FISD
Bond Rating	The S&P rating assigned to a specific issue	Mergent FISD
Maturity	Date that the issue's principal is due for repayment	Mergent FISD
Offering Amount	The par value of debt initially issued	Mergent FISD
Offering date	Date the issue was originally offered	Mergent FISD
Loan Characteristics		
Loan rate	Sum of "All-in-drawn" and LIBOR	DealScan
"All-in-drawn"	The amount borrower pays in basis points over LIBOR for each dollar drawn down	DealScan
Base Rate	Type of interest rate the company's facility is tied to	DealScan
Facility Amount	The actual facility amount committed by the facility's lender pool	DealScan
Maturity	A calculation of how long (in months) the facility will be active from signing date to expiration date	DealScan
Secured	A Y/N flag indicating whether or not the facility is secured	DealScan

A.2 Details on Model

A.2.1 General Equilibrium Model

Representative Household

There is a unit measure continuum of identical households with preferences over consumption C_t and total labor supply L_t, whose expected utility is as follows:

$$\sum_{t=0}^{\infty} \beta^t (logC_t - \Psi L_t),$$

subject to the budget constraint:

$$P_t C_t + \frac{B_{t+1}^{f,nom}}{R_t^{nom}} \le W_t L_t + B_t^{f,nom} + T_t^{nom},$$

where β is the discount factor of households, Ψ is the disutility of working, P_t is the price index, R_t^{nom} is the nominal rate, W_t is the nominal wage rate, $B_t^{f,nom}$ is the one-period risk-free bond in nominal terms, and T_t^{nom} is the transfer from all firms including the nominal profits. The budget constraint in the real term is

$$C_t + \frac{B_{t+1}^{f}}{R_t^{nom}} \Pi_{t+1} \le w_t L_t + B_t^{f} + T_t. \tag{A3}$$

Every period, the households make a decision on labor supply, which determines the real wage in the following optimal condition:

$$w_t = \frac{W_t}{P_t} = -\frac{U_l(C_t, L_t)}{U_c(C_t, L_t)} = \Psi C_t.$$

The decision over consumption and saving (through a risk-free bond) determines the discount factor, which is linked to nominal and inflation rates through the Euler equation:

$$\Lambda_{t,t+1} = \beta \frac{U_c(C_{t+1}, L_{t+1})}{U_c(C_t, L_t)} = \beta \frac{C_t}{C_{t+1}} = \frac{1}{R_t^{nom}/\Pi_{t+1}}.$$

New Keynesian Block

The New Keynesian block of the model consists of a final good producer who produces final goods, retailers who have quadratic adjustment costs when setting prices (price rigidity), and a monetary authority who sets the interest rate rule. It generates 1) a New Keynesian Phillips curve relating nominal variables to the real economy and 2) a Taylor rule, which links the monetary policy shock and inflation to the nominal interest rate.

Final Good Producer

There is a representative final good producer who produces the final good Y_t using intermediate goods from all retailers with the production function:

$$Y_t = \left(\int \tilde{y}_{i,t}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}},$$

where γ is the elasticity of substitution between intermediate goods. The final good producer solves the following profit maximization problem subject to the equation above:

$$\max_{\tilde{y}_{i,t}} \; P_t Y_t - \int_0^1 \tilde{p}_{i,t} \tilde{y}_{i,t} di.$$

The optimal decision gives the demand curve $\tilde{y}_{i,t} = \left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma} Y_t$ where the price index is $P_t = \left(\tilde{p}_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}$. The final good serves as the numeraire in the model.

Intermediate Retailers

For each production firm j, there is a corresponding retailer i who produces a differentiated variety $\tilde{y}_{i,t}$ using homogeneous good $y_{i,t}$ from production firm i as its only input:

$$\tilde{y}_{i,t} = y_{i,t},$$

where the retailers are monopolistic competitors who set their prices $\tilde{p}_{i,t}$ subject to the demand curve generated by the final good producer and the wholesale price of the input P_t. Retailers pay a quadratic menu cost in term of final good $\frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t$, to adjust their prices as in Rotemberg (1982), where Y_t is the final good.

The resulting price stickiness comes from the price-setting decisions made by retailers to maximize profits. I follow Rotemberg (1982) except the marginal cost is now the wholesale price

$$\pi_{i,t} = (\tilde{p}_{i,t} - p_t)\tilde{y}_{i,t} - \frac{\psi}{2}\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)^2 P_t Y_t.$$

Every period, the retailers choose a price to maximize the expected present value of all the future profit:

$$\max_{\tilde{p}_{j,t}} \; \mathbb{E}_t \sum \Lambda_{t,t+j} \pi_{t+j},$$

which gives the following New Keynesian Phillips curve:

$$log\Pi_t = \frac{\gamma - 1}{\psi} log \frac{p_t}{p^\star} + \beta \mathbb{E}_t log \Pi_{t+1},$$

where $p^* = \frac{\gamma-1}{\gamma}$ is the steady-state wholesale price, or in other words, the marginal cost for retailer firms. The Phillips curve links the New Keynesian block to the production block through the relative real wholesale price p^* for production firms. If the expectation of future inflation is unchanged, when the final good Y_t increases, retailers must increase production of their differentiated goods because of the nominal rigidity. This, in turn, increases demand for the production goods $\tilde{y}_{i,t}$, which increases the real wholesale price p_t and generates inflation through the Phillips curve.

Market Clearing Conditions

Consumption Good

$$C_t + I_t + DIC_t + EIC_t + AC_t + c_f = Y_t \tag{A4}$$

Labor

$$\int l_{i,t} d\mu_t = L_t \tag{A5}$$

Debt

$$\int \left(Q_t^l b_{i,t}^l + Q_t^b b_{i,t}^b\right) d\mu_t = \frac{B_t^f}{R_t^{nom}} \Pi_{t+1} \tag{A6}$$

where $b_{i,t}^l = B_{i,t}^l \left(1 - s_{i,t}\right)$ is the firm-level bank loans and $b_{i,t}^b = B_{i,t}^b s_{i,t}$ is the firm-level corporate bonds. The financial intermediary takes deposit from the household and lend it in terms of one-period bonds and loans to firms.

A.2.2 Propositions

Proof of Proposition 1

Proof. The optimal condition for the price-setting rule is

$$(\gamma - 1)\left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma} \frac{Y_t}{P_t} = \gamma \frac{p_t^w}{P_t}\left(\frac{\tilde{p}_{i,t}}{P_t}\right)^{-\gamma-1} \frac{Y_t}{P_t} - \psi\left(\frac{\tilde{p}_{i,t}}{\tilde{p}_{i,t-1}} - 1\right)\frac{Y_t}{\tilde{p}_{i,t-1}} + \mathbb{E}_t \psi \Lambda_{t,t+1}\left[\left(\frac{\tilde{p}_{i,t+1}}{\tilde{p}_{i,t}} - 1\right)\frac{\tilde{p}_{i,t+1}}{\tilde{p}_{i,t}}\frac{Y_{t+1}}{\tilde{p}_{i,t}}\right].$$

With the symmetric assumption $\tilde{p}_{i,t} = \tilde{p}_{j,t} = P_t$, the above equation can be written as

$$(\gamma - 1) = \gamma \frac{p_t^w}{P_t} - \psi \Pi_t (\Pi_t - 1) + \mathbb{E}_t \psi \Lambda_{t,t+1} \Pi_{t+1} (\Pi_{t+1} - 1) \frac{Y_{t+1}}{Y_t},$$

which gives the Phillips curves:

$$\left(\Pi_t - \bar{\Pi}\right)\Pi_t = \frac{\gamma}{\psi}\left(p_t^w - \frac{\gamma - 1}{\gamma}\right) + \mathbb{E}_t \Lambda_{t,t+1} \Pi_{t+1} (\Pi_{t+1} - \bar{\Pi}) \frac{Y_{t+1}}{Y_t},$$

where $p_t = \frac{p_t^w}{P_t}$ is the real wholesale price. The log-linearized steady-state version of the Phillips curves (for computation simplicity) is

$$log\Pi_t = \frac{\gamma - 1}{\psi} log \frac{p_t}{p^\star} + \beta \mathbb{E}_t log \Pi_{t+1}.$$

□

Proof of Proposition 2

Proof. Combining the Euler equation

$$logR_t + log\beta = log\Pi_{t+1} - log\frac{U'(C_{t+1})}{U'(C_t)},$$

and the Taylor rule

$$logR_t + log\beta = \psi_\pi log\Pi_t + \epsilon_t^m,$$

we get

$$\psi_\pi log\Pi_t + \epsilon_t^m = log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right),$$

which is

$$\Pi_t = exp\left(\frac{1}{\psi_\pi}\left[log\left(\Pi_{t+1}\frac{U'(C_t)}{U'(C_{t+1})}\right) - \epsilon_t^m\right]\right).$$

□

Proof of Proposition 6

Proof.

$$B_{i,t+1}(1-s_{i,t+1})(1+c) \leq \theta(1-\delta)k_{i,t+1},$$

which gives

$$s_{i,t+1} \in \left[1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)}, 1\right].$$

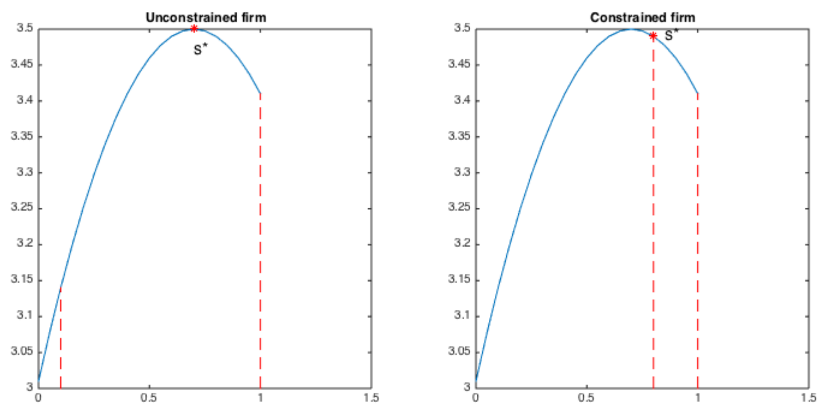
When firms are charged the same price, that is, $Q^b_{i,t} = Q^l_{i,t}$, $\forall s_{i,t+1}$,

$$\frac{\partial F}{\partial s_{i,t+1}} = \xi_0 - \xi_1 > 0, \ \ \forall s_{i,t+1} \in \left[1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)}, 1\right].$$

Therefore,

$$s^*_{i,t+1} = argmax \ \ F(s_{i,t+1}; z_{i,t}, k_{i,t+1}, B_{i,t+1}) = 1.$$

□



Proof of Proposition 7

Proof. Given $(k_{i,t}, B_{i,t}, z_{i,t}; \beta_t)$,

$$\frac{\partial F}{\partial s_{i,t+1}}|_{s_{i,t+1}=0} = \xi_0 - \xi_1 > 0 \ \text{ and } \ s_{i,t+1} \in \left[1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)}, 1\right].$$

i) If $\frac{\partial F}{\partial s_{i,t+1}}|_{s_{i,t+1}=1} \geq 0$, then $s^*_{i,t+1} = 1$.

ii) If $\frac{\partial F}{\partial s_{i,t+1}}|_{s_{i,t+1}=1} \leq 0$, set $\frac{\partial F}{\partial s_{i,t+1}} = 0$ gives

$$\hat{s} = \frac{(\xi_0 - \xi_1) + (Q^b_{i,t} - Q^l_{i,t})}{\frac{\partial Q^l_{i,t}}{\partial \hat{s}_{i,t+1}} - \frac{\partial Q^b_{i,t}}{\partial \hat{s}_{i,t+1}}}.$$

Then $s^*_{i,t+1} = \hat{s} < 1$. Therefore, the optimal bond share

$$s^*_{i,t+1} = argmax\ F(s_{i,t+1}; z_{i,t}, k_{i,t+1}, B_{i,t+1}) > 0.$$

a) For unconstrained firms with lower leverage, that is, $1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)} < \hat{s}$, the optimal decision is

$$s^*_{i,t+1} = 1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)},$$

b) For constrained firms with higher leverage, that is, $1 - \frac{\theta(1-\delta)k_{i,t+1}}{B_{i,t+1}(1+c)} \geq \hat{s}$, the optimal decision is

$$s^*_{i,t+1} = \hat{s}.$$

Also see the figure above. □

A.3 Details on Numerical Solution

A.3.1 Steady-State Equilibrium

In this section, I outline the numerical algorithm I use. I solve for the steady-state equilibrium by value function iteration. The value function and the optimal decision rules are solved on a grid in a discrete state space with interpolation. I discretize the state space $\mathbb{S} = (z, k, B)$ into $n_z \times n_k \times n_B$ grid points. Specifically, I specify two grids of 30 points ($n_k = n_B = 30$) for capital k and total debt B, with upper bounds that are large enough to be nonbinding. I assign more grid points around lower bounds, where the value function has most of its curvature. For interpolation, I specify two grids of 200 points for investment k' and total borrowing B'. I also specify a grid of 151 points for bond share s' for the static optimization problem for debt structure. I then discretize the exogenous productivity according to Rouwenhorst (1995). I use 5 grid points ($n_z = 5$) for the idiosyncratic productivity states. In the steady-state equilibrium, the discount factor is β, the inflation rate is $\Pi^\star = 1$, and the wholesale price is $p^\star = \frac{\gamma-1}{\gamma}$. The nominal rate and the real rate are therefore $1/\beta - 1$. The computational algorithm—following Strebulaev and Whited (2012)— proceeds as follows:

Start outer loop

1. Guess a default policy $D_{t+1}(z', k', B')$ and compute the implied bond prices $Q_t(z, k', B', s')$ based on lenders' zero-profit condition.

   Start inner loop

   (a) Given the default policy and bond price, have an initial guess for the expected value $E_z V^0_{t+1}(z, k', B')$.
   (b) Given (z, k, B, k', B'), solve the static loan-bond trade-off problems and get the optimal bond share $s'(z, k', B')$.

(c) With s', solve the maximization problem for optimal investment and borrowing decisions $k'(z,k,B)$, $B'(z,k,B)$ and value function $V_t(z,k,B)$.

2. Obtain $V_{t+1}^{new}(z',k',B')$ by interpolation and update the default decision $D_{t+1}^{new}(z',k',B')$ (here, V and D do not depend on s'), expected value function $E_z V_{t+1}^{new}(z,k',B')$, and bond price $Q_t^{new}(z,k',B',s')$.
3. Compute the ergodic distribution $\mu(z,k,B)$ implied by the firm policies for default, capital and borrowing: $D(z,k,B)$, $k'(z,k,B)$, and $B'(z,k,B)$.
4. Iterate the above procedure until the error of the expected value function and default policy is small enough:
$\epsilon = max\left(|E_z V_{t+1}(z,k',B') - E_z V_{t+1}^{new}(z,k',B')|, |D_{t+1}(z',k',B') - D_{t+1}^{new}(z',k',B')|\right)$.

After convergence, I have the stationary equilibrium aggregate prices $\{\pi^\star = 1, \Lambda^\star = \beta, p^\star = \frac{\gamma-1}{\gamma}, R^\star = 1/\beta, w^\star = w^\star\}$, aggregate quantities $\{C^\star, L^\star, Y^\star, K^\star, I^\star, B^\star\}$, firm value function $V^\star(\mathbb{S})$, policy functions $k^{'\star}(\mathbb{S}), B^{'\star}(\mathbb{S}), l^\star(\mathbb{S}), s^{'\star}(\mathbb{S}), D^\star(\mathbb{S})$, and stationary distribution $\mu(\mathbb{S})$.

A.3.2 Transition Dynamics

The key assumption of the transition dynamics is that after a sufficiently long enough time, the economy will always converge back to its initial stationary equilibrium after any temporary and unexpected (MIT) shocks.

1. Generate a one-time positive interest rate shock of 25 basis points and assume the shock follows $\epsilon_{t+1}^m = \rho^m \epsilon_t^m$ with $\rho^m = 0.5$. Fix a sufficiently long transition period from $t = 1$ to $t = T$.
2. Guess a time path for marginal utility $U'(C_t)$ for $t = 1,2,...,T+1$ and set $U'(C_{T+1}) = U'(C^\star)$.
3. Set all the prices p, w, R, r in period $T+1$ to be their steady-state values. Given the inflation dynamics, obtain R_t from the Taylor rule, r_t from the Fisher equation, w_t from the labor market clearing condition, and p_t from Phillips curve for $t = 1,2,...,T$.
4. I assume a steady-state value and policy function in period $T+1$ and update the value and policy functions using **backward induction** given the price series for $t = 1,2,...,T$.
5. Given the policy functions and the steady-state distribution as the initial distribution, I use **forward simulation** with the non-stochastic simulation in Young (2010) to find the transition matrix T_t and distribution $\mu_t(\mathbb{S})$ for $t = 1,2,...,T$.
6. I obtain all the aggregate quantities along the time path using $\mu_t(\mathbb{S})$ and update $U'(C_t)$ using consumption good market clearing condition, as well as other price series for $t = 1,2,...,T$.

A.3.3 Simulated Method of Moments Estimation

To generate the simulated data for the SMM estimation (used to create $\Phi^S(\theta)$ in Equation (19)), I simulate an economy with 10,000 firms and 250 quarters, with the first 200 quarters discarded to eliminate the effects of any assumptions on initial conditions. I use a simulated annealing algorithm for minimizing the criterion function in the estimation step in Equation (19). This starts with a predefined first guess of the parameters θ. For the second guess onward, it takes the best prior guess and randomizes from this to generate a new set of parameter guesses. That is, it takes the best-fit parameters and randomly "jumps off" from this point for its next guess. Over time, the algorithm "cools" so that the variance of the parameter jumps falls, allowing the estimator to fine-tune its parameter estimates around the global best fit. I restart the program with different initial conditions to ensure the estimator converges to the global minimum. To generate the standard errors for the parameter point estimates, we generate numerical derivatives of the simulation moments with respect to the parameters and weigh them using the optimal weighting matrix. The value of the numerical derivative is computed as $f'(x) = \frac{f(x+\epsilon)-f(x-\epsilon)}{2\epsilon}$. [4] Here, I choose $\epsilon = 0.01x$.

A.3.4 Simulation

Model moments

To match the simulated model moments and their corresponding data moments, I simulate a sample panel of 5,000 firms for 200 quarters in total, including a 100-quarter burn-in period from the stationary equilibrium solutions. I exclude defaulting firms when I calculate the moments, except for the credit spread. I simulate 50 artificial samples and report the cross-sample average results as model moments in Table 1.6.

Dynamic responses

To replicate firms' differential responses in their financing decision to the interest rate shock, I simulate a panel of 5,000 firms using the updated value and policy functions along the transition path after a positive interest rate shock of 25 basis points. Specifically, I first simulate 5,000 firms for 50 quarters from initial arbitrage positions using stationary value and policy functions. Then in the 101^{th} quarter, I draw a shock of 25 basis points and simulate 5,000 firms for another 20 quarters using the updated value and policy functions along the transition path. I redo the main empirical analysis using this simulated sample. The above procedure is repeated 10 times, and the average of estimates is reported.

A.4 Additional Results

Appendix A.4 contains several sets of additional empirical results.

The first set of additional results contains two robustness checks of the aggregate analysis. Columns (1) to (4) of Table A.6 decompose the aggregate loans by maturity, showing that monetary shocks have a large and significant impact on short-term loans relative to long-term loans, mostly mortgages. Columns (5) to (8) decompose the measured monetary shocks, suggesting that it is the changes in the short rate ("target" component) rather than the changes in the long rate ("path" component) that drive the results.

The second set of additional results distinguish "financially constrained" firms from "unconstrained" firms using "Whited-Wu" (Whited and Wu (2006a)) and the Size & Age index (Hadlock and Pierce (2010), hereafter, the "HP" index). The results in Table A.7 confirm the robustness of differential adjustments in financing decisions in response to monetary shocks.

The third set of robustness checks discuss the measures of monetary shocks. The high-frequency identification method assumes that no other news is systematically released within the narrow windows around the FOMC announcement. However, the literature on the Fed information effect have called this assumption into question: they posits that the Federal Reserve systematically reveals new information about other economic fundamentals in its meeting announcements, in addition to the pure monetary policy news. Therefore, it is important to differentiate between the two effects. This is not likely to be an issue for two reasons. First, the Fed information effect became dominant after 2007 with the adoption of unconventional monetary policy. The significant results of the pre-crisis (1990-2007) sample analysis included in Table A.8 imply that the results are more likely to be driven by the changes in the short rate. Second, Jarociński and Karadi (2020) exploit the negative and positive co-movement between interest rates and stock prices to disentangle

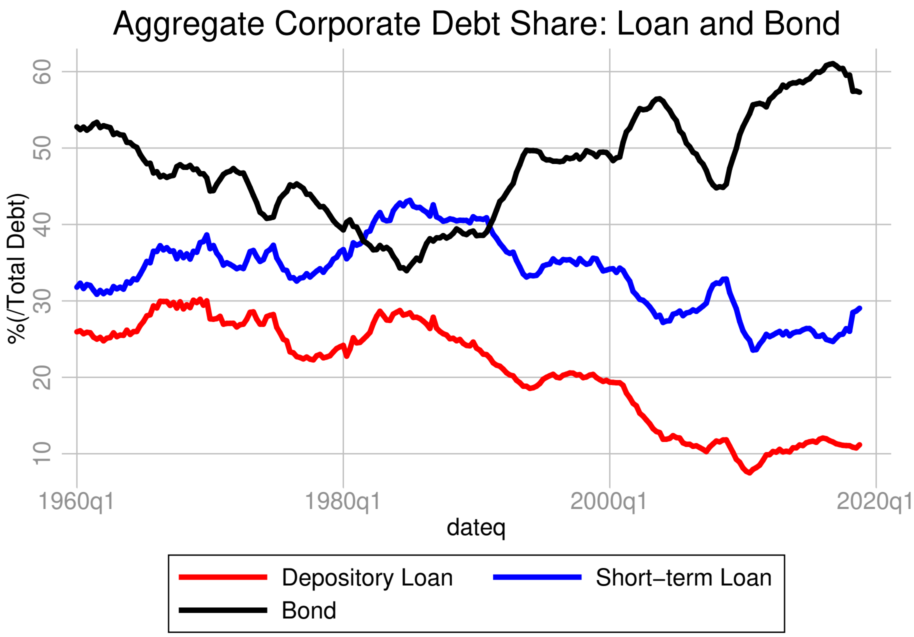
[4] The value of the numerical derivative is sensitive to the exact value of ϵ chosen. This is a common problem with calculating numerical derivatives using simulated data with underlying discontinuities, arising, for example, from grid-point-defined value functions.

the pure monetary policy effect from the Fed information effect. The correlation between S&P 500 stock return and the pure monetary shocks, information shocks are -0.45 and 0.23, respectively. I employ the pure monetary policy shocks constructed in Jarociński and Karadi (2020) and the results are presented in Figure A.4. Policy news shocks from Nakamura and Steinsson (2018) give similar conclusions, as shown in Table A.9.

Business cycle and monetary cycle are overlapped. The correlation between GDP growth and monetary shocks is reasonably low in this sample. To rule out the business cycle effect, I also control for a set of macroeconomic variables. In addition, Table A.10 shows the asymmetric effects of monetary policy, and it suggests that most of the results are driven by expansionary periods. The effects of monetary policy on firm-level borrowing costs, cash holding, trade credit, dividend payout decision, and excess stock return are presented in Table A.11 and Table A.12.

Figure A.1. Aggregate Time Series of Corporate Debt

This figure plots the time series of debt ratio: loan/total debt and bond/total debt of the nonfinancial corporate sector from 1960Q1 to 2018Q4. Total debt is defined as the sum of debt securities and loans. Data are obtained from the Flow of Funds L.103. Corporate bonds and loans are negatively correlated. A shift from bank debt to market debt takes place over time.



Nonfinancial corporate business	1980Q1	2008Q2	2018Q4
Debt securities	412	3,499	6,310
Commercial paper	31	140	196
Municipal securities	37	404	571
Corporate bonds	344	2,955	5,542
Loans	463	3,070	3,339
Depository institution loans n.e.c.	212	759	1,003
Other loans and advances	110	1,362	1,710
Total mortgages	142	949	626

Figure A.2. Aggregate Time Series of Corporate Debt: Other Types

This figure plots the time series of other types of corporate debt from 1975Q1 to 2018Q4. It includes Commercial and Industrial (C&I) loans, commercial paper, consumer loans, and real estate loans. Data are obtained from the St. Louis Fed's FRED database.

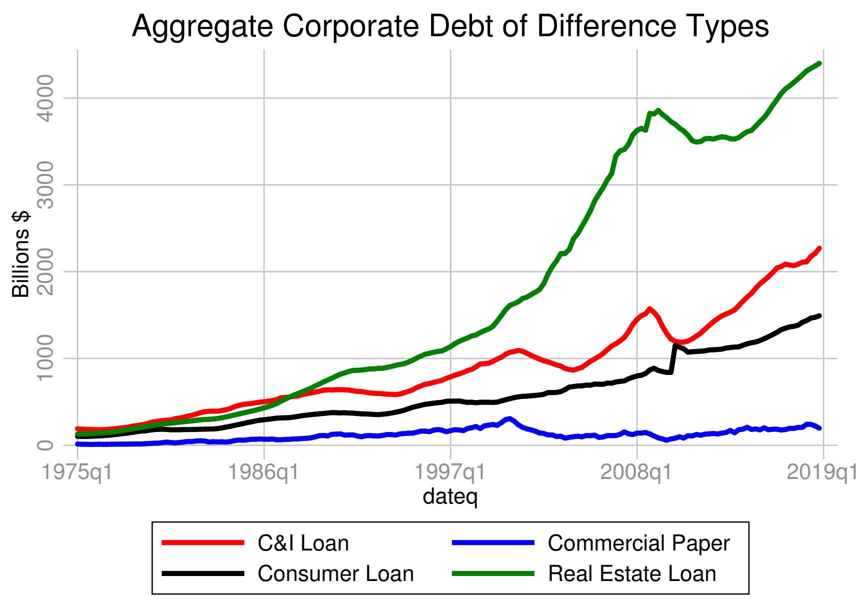


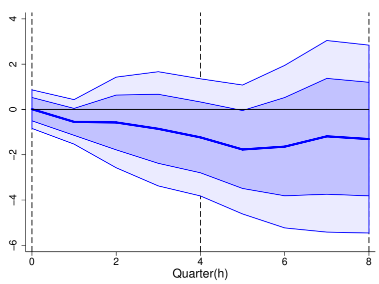
Figure A.3. Dynamic Effects of Monetary Shocks on Debt

These figures plot the impulse responses to a one-standard-deviation monetary shock ϵ_t^m based on the identification approach by Gürkaynak et al. (2005) and Gorodnichenko and Weber (2016) at a quarterly frequency and the local projection specification. Coefficient estimates β_h from the following regressions are plotted over time horizon h:

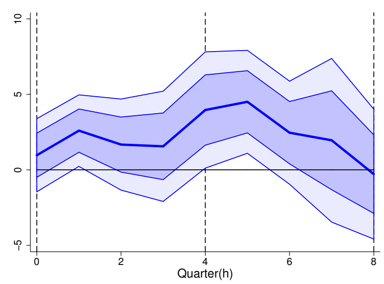
$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \epsilon_t^m + \Gamma_h Controls_{t-1} + \epsilon_{t+h},$$

where $h = 0, 1, 2, ..., 8$, and y is the log(real credit). The control variables include one year of lagged values of the monetary policy shock and one year of lagged values of the one-quarter change in the respective dependent variable, real GDP growth, inflation rate, unemployment, term spread, SLOOS tightening standards, and the forecasts of GDP growth and unemployment. The shaded areas are 68% and 90% error bands. The debt series are obtained from the Flow of Funds L.103 and the St. Louis Fed. The sample covers the periods from 1990Q2 to 2018Q4.

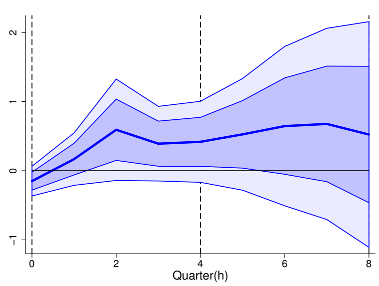
(a) β_h for Mortgages (%)



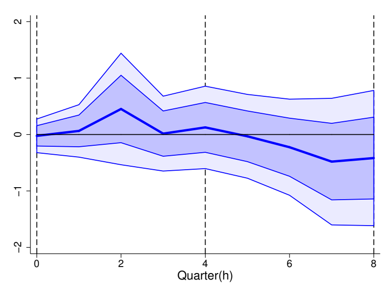
(b) β_h for Commercial Paper (%)



(c) β_h for Commercial & Industrial Loans (%)



(d) β_h for Real Estate Loans (%)



(e) β_h for Trade Credit (%)

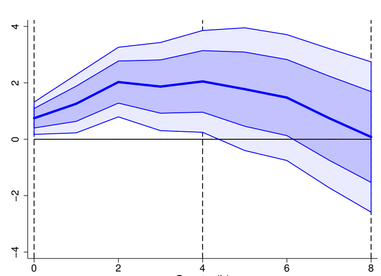


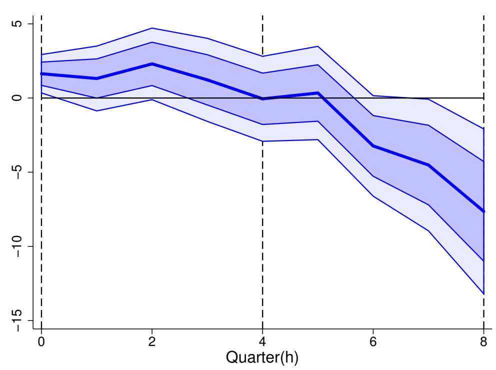
Figure A.4. Dynamic Effects of Pure Interest Rate Shocks and Information Shocks

These figures plot the impulse responses to a one-standard-deviation pure interest rate shocks and information shocks ϵ_t^m based on the identification approach by Jarociński and Karadi (2020) at a quarterly frequency and the local projection specification. Coefficient estimates β_h from the following regressions are plotted over time horizon h:

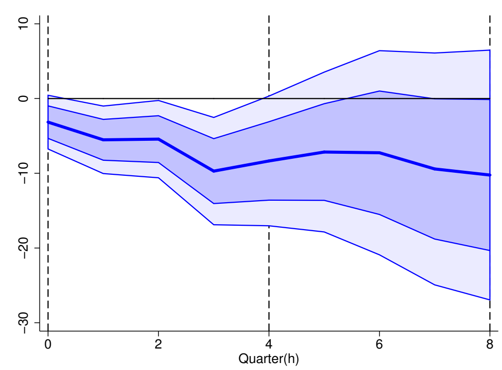
$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \epsilon_t^m + \Gamma_h Controls_{t-1} + \epsilon_{t+h},$$

where $h = 0, 1, 2, ..., 8$, and y is the real credit (Billions of 1982 U.S. Dollars). The control variables include one year of lagged values of the monetary policy shock and one year of lagged values of the one-quarter change in the respective dependent variable, real GDP growth, inflation rate, unemployment, term spread, SLOOS tightening standards, and the forecasts of GDP growth and unemployment. The shaded areas are 68% and 90% error bands. The debt series are obtained from the Flow of Funds L.103. The sample covers the periods from 1990Q2 to 2018Q4.

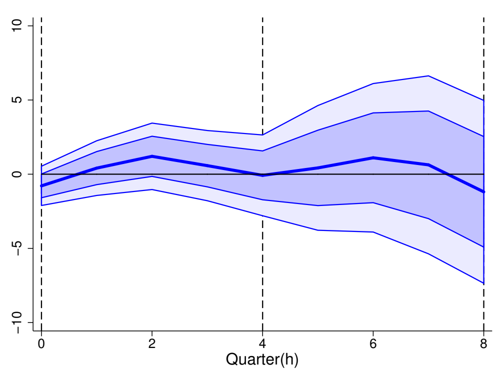
(a) Monetary policy: β_h for Bank Loans



(b) Monetary policy: β_h for Corporate Bonds



(c) CB information: β_h for Bank Loans



(d) CB information: β_h for Corporate Bonds

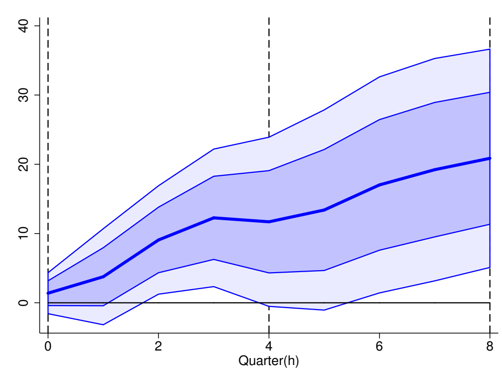
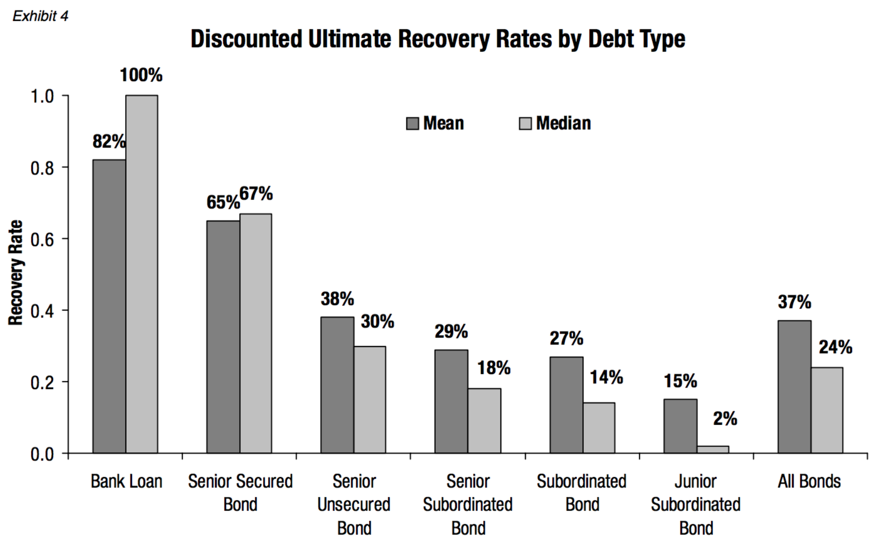


Figure A.5. Moody's Recovery by Debt Type

As can be seen in Exhibit 4, bank loans recover an average of 82 percent at a resolution on a discounted basis with a corresponding median of 100 percent. In contrast, senior secured bonds recover an average of 65 percent with a median of 67 percent. Discounted ultimate recovery rates on bonds vary from 38 percent for senior unsecured bonds to 15 percent for junior subordinated bonds. Across all bonds, the average recovery rate is 37 percent, with a median of 24 percent. Exhibit 5 shows the distributions of loan and bond recovery rates, indicating strong skewness in both distributions whereby the probability of full recovery for loans is relatively high, and the probability of low recovery for bonds is also relatively high. **Source: Moody's recovery database**



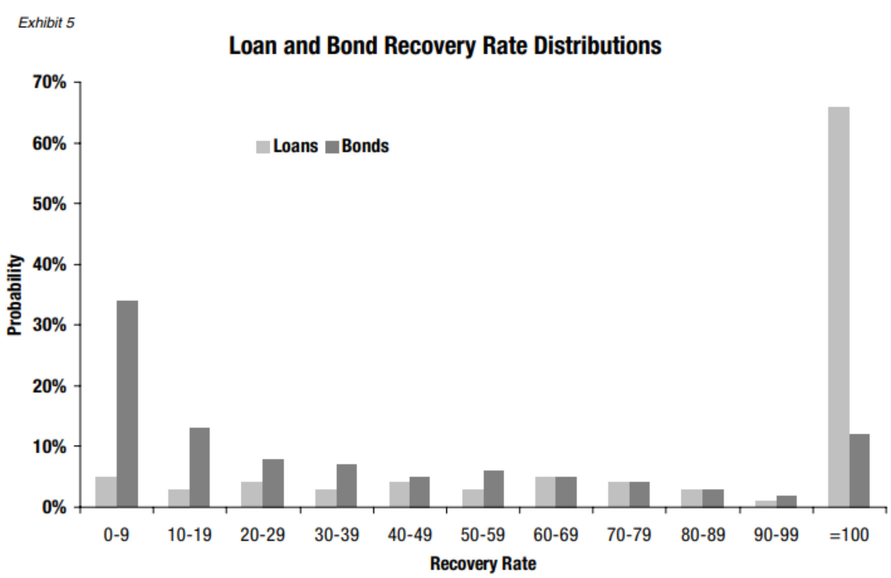


Table A.2. Robustness Check: Loans and Bonds Issuances

This table reports firms' loans and bonds issuance decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

where $y_{i,t}$ is a dummy equal to one if the firm chooses to issue new loans (columns (1) to (4)) or issues new bonds (columns (5) to (8)) in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm's size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prob(issue new loans)				Prob(issue new bonds)			
ϵ_t^m	0.006***	0.007***	0.006***	0.007***	-0.002	-0.004**	0.006***	-0.004**
	(9.402)	(9.492)	(8.498)	(10.017)	(-1.390)	(-2.367)	(3.836)	(-2.332)
$\epsilon_t^m \times$ Size		0.003***				-0.008***		
		(3.550)				(-4.024)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.002				-0.022***	
			(1.359)				(-6.052)	
$\epsilon_t^m \times$ D2D				0.002***				-0.005***
				(2.852)				(-3.362)
Observations	158998	158998	158998	158998	53710	53710	53710	53710
R^2	0.045	0.045	0.045	0.045	0.136	0.137	0.138	0.137
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table A.3. Robustness Check: Debt Financing Decision in Logistic Regression

This table reports firms' differential debt financing decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following *logistic* regressions.

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

where $y_{i,t}$ is a dummy equal to one if the firm chooses bank loans over corporate bonds in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm's size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
	Prob(Borrow from bank)			
ϵ_t^m	0.135***	0.140***	-0.009	0.165***
	(4.838)	(4.839)	(-0.178)	(5.682)
$\epsilon_t^m \times$ Size		0.073**		
		(2.307)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.223***	
			(3.735)	
$\epsilon_t^m \times$ D2D				0.122***
				(3.888)
Observations	9042	9042	9042	9042
Firm & Aggregate controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y

Table A.4. Robustness Check: Maturity Basket

This table reports the impact of monetary shocks on debt financing decisions and borrowing costs over a subsample of new issuances with maturities between 3 and 8 years. Coefficients are estimated from the following regressions.

$$\begin{aligned} Credit\ Spread_{j,t} =& \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta(X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,t-1} + \Gamma_3' Y_{t-1} + \epsilon_{j,t}. \end{aligned}$$

In panel A, columns (1) to (4) report the results of loan spreads, which is the difference between the loan rate and the three-month LIBOR. Columns (5) to (8) report the results of bond spreads, which is the difference between offering yield and the three-month LIBOR. Panel B reports the results of firms' choices between loans and bonds. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is the firm size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. $W_{j,t-1}$ is a set of debt characteristics including the logarithm of borrowing amount and maturity. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Credit Spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Spread				Bond Spread			
ϵ_t^m	0.047***	0.057***	0.043***	0.063***	0.204***	0.216***	0.083	0.212***
	(4.778)	(5.580)	(3.323)	(6.228)	(4.839)	(5.014)	(0.764)	(5.151)
$\epsilon_t^m \times$ Size		0.012				-0.038		
		(1.342)				(-0.953)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.043**				0.120	
			(2.276)				(1.037)	
$\epsilon_t^m \times$ D2D				0.025**				0.031
				(2.024)				(0.636)
Observations	13425	13425	13425	13425	2763	2763	2738	2763
R^2	0.693	0.694	0.694	0.694	0.690	0.691	0.705	0.692
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Extensive margin	(1)	(2)	(3)	(4)
	Prob(Borrow from bank)			
ϵ_t^m	0.021***	0.023***	0.009	0.025***
	(3.764)	(3.963)	(1.130)	(4.278)
$\epsilon_t^m \times$ Size		0.011**		
		(2.437)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.023**	
			(2.173)	
$\epsilon_t^m \times$ D2D				0.006
				(1.080)
Observations	7890	7890	7890	7890
R^2	0.418	0.419	0.419	0.418
Firm & Aggregate controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y

Table A.5. Robustness Check: Relationship Lending

This table reports the impact of monetary shocks on debt financing decisions and loan spreads. Coefficients are estimated from the following regressions.

$$
\begin{aligned}
y_{j,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times REL(M)_{i,k,j,t} + \eta \Delta GDP_t \times REL(M)_{i,k,j,t} \\
&+ \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{j,t-1} + \Gamma_3' Y_{t-1} + \epsilon_{j,t}.
\end{aligned}
$$

The relationship strength is defined as

$$
REL(Amount)_{i,k,j,t} = \frac{\text{Amount of loans by lender i to borrower j in the last 5 years(\$)}}{\text{Total amount of loans by borrower j in the last 5 years(\$)}},
$$

$$
REL(Number)_{i,k,j,t} = \frac{\text{Number of loans by lender i to borrower j in last 5 years}}{\text{Total number of loans by borrower j in last 5 years}},
$$

and $REL(Dummy)$ equals to one when $REL(Amount)_{i,k,j,t}$ is positive. Columns (1) to (4) report the results of firms' choices between loans and bonds. Columns (5) to (8) report the results of loan spreads, which is the difference between the loan rate and the three-month LIBOR. ϵ_t^m is the monetary shock, and $REL(M)_{i,k,j,t}$ is the measure of relationship strength. $Z_{i,t-1}$ is a set of firm control variables including size, distance to default, market-to-book ratio, liquidity, tangibility, leverage, a dummy for dividend payout, and a dummy for credit rating. $W_{j,t-1}$ is a set of debt characteristics including the logarithm of borrowing amount and maturity. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prob(Borrow from bank)				Loan Spread			
ϵ_t^m	0.018***	0.016***	0.020***	0.017***	0.019**	0.048***	0.049***	0.047***
	(4.084)	(3.181)	(3.887)	(3.371)	(2.480)	(4.801)	(4.525)	(4.673)
$\epsilon_t^m \times$ REL(Amount)		0.013				-0.084***		
		(1.029)				(-4.325)		
$\epsilon_t^m \times \mathbb{1}$(REL)			-0.005				-0.057***	
			(-0.581)				(-3.988)	
$\epsilon_t^m \times$ REL(Number)				0.009				-0.085***
				(0.703)				(-4.253)
Observations	11850	11850	11850	11850	17429	17429	17429	17429
R^2	0.396	0.399	0.400	0.399	0.722	0.723	0.723	0.723
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table A.6. Robustness Check: Aggregate Time Series Analysis

This table reports the effect of monetary shocks on aggregate debt in quarter t. Coefficients are estimated from the following regressions.

$$\Delta y_t = \alpha + \beta \epsilon_t^m + \Gamma Controls_{t-1} + \epsilon_t.$$

Columns (1) to (4) report the effects of monetary shocks ϵ_t^m on the flows of short-term and long-term loans in quarter t. Columns (5) to (8) report the separate effects of the target and path components of monetary shocks on the flows of loans and bonds. Nonfinancial corporate sector debt series are obtained from the Flow of Funds L.103. Other control variables include lagged values of the dependent variable, real GDP growth, inflation rate, unemployment, term spread, price-dividend ratio, and the forecasts of GDP growth. Monetary shocks are standardized. The sample of columns (1) to (4) covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The sample of columns (5) to (8) covers periods from 1990Q2 to 2004Q4. The t-statistics are in parentheses. All the variables are real. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Short-term versus Long-term Loan				Shock: Target versus Path			
					Target		Path	
	$\Delta STLoan$		$\Delta LTLoan$		$\Delta Loan$	$\Delta Bond$	$\Delta Loan$	$\Delta Bond$
ϵ_t^m	4.942***	5.516***	0.510	0.531				
	(2.985)	(3.304)	(0.611)	(0.590)				
ϵ_t^m(Target)					3.214***	-3.956**		
					(3.762)	(-2.435)		
ϵ_t^m(Path)							0.419	-0.221
							(0.348)	(-0.115)
ΔGDP_{t-1}	497.887	407.245	-57.942	-210.012	99.670	90.551	329.663*	-231.889
	(1.473)	(1.035)	(-0.279)	(-0.943)	(0.667)	(0.275)	(1.819)	(-0.681)
ΔCPI_{t-1}	900.387*	631.595	250.543	187.860	233.356	-661.484	105.047	-459.080
	(1.876)	(1.199)	(0.687)	(0.514)	(0.794)	(-1.025)	(0.308)	(-0.677)
UNEMP_{t-1}	-4.123**	-2.624	-3.585***	-3.319***	-1.217	11.927*	-2.777	13.544*
	(-2.134)	(-1.009)	(-4.705)	(-2.850)	(-0.306)	(1.791)	(-0.679)	(1.783)
Term Spread_{t-1}		-5.140**		-0.256	-1.105	-9.619**	0.698	-11.201**
		(-2.148)		(-0.184)	(-0.410)	(-2.283)	(0.238)	(-2.311)
$\text{Price-Dividend}_{t-1}$		-0.111		0.063	-0.100	0.431*	-0.139	0.476
		(-0.738)		(0.726)	(-0.552)	(1.743)	(-0.764)	(1.597)
GDP Forecast_{t-1}		0.764		0.729	0.317	-0.815	0.142	-0.599
		(0.795)		(1.566)	(0.656)	(-1.376)	(0.295)	(-0.942)
Observations	110	110	110	110	58	58	58	58
Adjusted R^2	0.254	0.254	0.285	0.287	0.586	0.311	0.512	0.257

Table A.7. Robustness Check: Financing Decisions and Financial Constraints

This table reports firms' differential debt and equity financing decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$y_{i,t} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}.$$

Columns (1) to (5) report financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm chooses bank loans over corporate bonds (panel A) or issues new equity (panel B) in quarter t. Columns (6) to (10) report firm financing decisions on the intensive margin, where the *dependent variable* is the growth rate of loans (panel A) or equity share (panel B) in quarter t. Financial constraints are measured by the "Whited-Wu" index or the "HP" index. Columns (2), (3), (7), and (8) show results for financially constrained firms, while columns (4), (5), (9), and (10) show results for financially unconstrained firms. ϵ_t^m is the monetary shock and $Z_{i,t-1}$ is a set of firm control variables including size, market-to-book ratio, liquidity, tangibility, leverage, distance to default, a dummy for dividend payout, and a dummy for investment grade firms. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	The Extensive Margin					The Intensive Margin				
	(1) Full Sample	(2) Constrained Firms Top Tercile	(3)	(4) Unconstrained Firms Bottom Tercile	(5)	(6) Full Sample	(7) Constrained Firms Top Tercile	(8)	(9) Unconstrained Firms Bottom Tercile	(10)
		WW	HP	WW	HP		WW	HP	WW	HP
Panel A: Debt Financing	Prob(Borrow from bank)					Δlog(Loan)				
ϵ_t^m	0.014***	-0.006	-0.003	0.012*	0.031***	0.275***	0.119	0.097	0.452***	0.420***
	(3.130)	(-0.726)	(-0.353)	(1.691)	(4.383)	(3.332)	(1.022)	(0.790)	(3.158)	(3.096)
Observations	11850	3392	3357	4161	4401	184939	52769	48611	70801	73011
R^2	0.400	0.477	0.484	0.388	0.361	0.094	0.171	0.186	0.092	0.084
Panel B: Equity Financing	Prob(Net new issuance)					ΔEquity share				
ϵ_t^m	0.215***	0.516***	0.612***	-0.058	-0.016	0.124***	0.162***	0.200***	0.080***	0.075***
	(4.469)	(4.472)	(4.766)	(-0.928)	(-0.266)	(6.322)	(2.807)	(2.898)	(4.366)	(4.174)
Observations	298562	87664	81327	112169	116547	241814	63221	56969	101215	103831
R^2	0.141	0.202	0.208	0.085	0.066	0.133	0.168	0.176	0.116	0.102
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A.8. Robustness Check: Pre-crisis Periods (1990-2007)

This table reports firms' differential debt and equity financing decisions in response to monetary shocks in quarter t. Coefficients are estimated from the following regressions.

$$y_{i,t} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \delta(X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}.$$

Columns (1) to (4) report financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm chooses bank loans over corporate bonds (panel A) or issues new equity (panel B) in quarter t. Columns (5) to (8) report financing decisions on the intensive margin, where the *dependent variable* is the growth rate of loans (panel A) or equity share (panel B) in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2007Q4. The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and *t*-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	The Extensive Margin				The Intensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Debt Financing	Prob(Borrow from bank)				Δlog(Loan)			
ϵ_t^m	0.021***	0.019***	0.000	0.025***	0.387***	0.330***	0.257**	0.376***
	(4.126)	(3.687)	(0.015)	(4.651)	(3.955)	(3.436)	(2.482)	(3.826)
$\epsilon_t^m \times$ Size		0.016***				0.227***		
		(3.242)				(2.784)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.035***				0.563**	
			(3.568)				(2.356)	
$\epsilon_t^m \times$ D2D				0.027***				0.279***
				(5.216)				(3.041)
Observations	8414	8414	8414	8414	138677	138677	138677	138677
R^2	0.466	0.467	0.467	0.468	0.113	0.113	0.114	0.114
Panel B: Equity Financing	Prob(Net new issuance)				ΔEquity share			
ϵ_t^m	0.304***	0.312***	0.301***	0.196***	0.109***	0.110***	0.106***	0.091***
	(5.061)	(5.029)	(4.608)	(2.998)	(4.407)	(4.080)	(3.855)	(3.684)
$\epsilon_t^m \times$ Size		-0.154***				-0.069***		
		(-2.607)				(-2.663)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			-0.034				-0.052	
			(-0.265)				(-1.374)	
$\epsilon_t^m \times$ D2D				-0.019				-0.103***
				(-0.350)				(-4.679)
Observations	226091	226091	226091	184689	184684	184684	184684	184684
R^2	0.143	0.143	0.143	0.152	0.149	0.149	0.149	0.149
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table A.9. Robustness Check: Financing Decisions and Policy News Shocks

This table reports firms' differential debt and equity financing decisions in response to policy news shocks from Nakamura and Steinsson (2018) in quarter t. Coefficients are estimated from the following regressions.

$$y_{i,t} = \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \delta(X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}.$$

Columns (1) to (4) report financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm chooses bank loans over corporate bonds (panel A) or issues new equity (panel B) in quarter t. Columns (5) to (8) report financing decisions on the intensive margin, where the *dependent variable* is the growth rate of loans (panel A) or equity share (panel B) in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm's size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1995Q1 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	The Extensive Margin				The Intensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Debt Financing	Prob(Borrow from bank)				Δlog(Loan)			
ϵ_t^m	0.003	0.004	0.002	0.007	0.518***	0.572***	0.283***	0.517***
	(0.703)	(0.878)	(0.382)	(1.532)	(6.533)	(6.937)	(3.391)	(6.395)
$\epsilon_t^m \times$ Size		0.001				0.535***		
		(0.360)				(6.861)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.002				1.280***	
			(0.284)				(5.624)	
$\epsilon_t^m \times$ D2D				0.008*				0.139
				(1.748)				(1.601)
Observations	11707	11707	11707	11707	152065	152065	152065	152065
R^2	0.391	0.391	0.391	0.391	0.101	0.102	0.102	0.101
Panel B: Equity Financing	Prob(Net new issuance)				ΔEquity share			
ϵ_t^m	0.279***	0.274***	0.288***	0.213***	0.200***	0.184***	0.207***	0.136***
	(5.479)	(5.524)	(5.168)	(3.849)	(8.877)	(8.375)	(8.163)	(5.938)
$\epsilon_t^m \times$ Size		-0.130**				-0.087***		
		(-2.483)				(-3.297)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.014				-0.137***	
			(0.130)				(-3.816)	
$\epsilon_t^m \times$ D2D				-0.028				-0.189***
				(-0.507)				(-8.127)
Observations	251505	251505	251505	201595	201585	201585	201585	201585
R^2	0.150	0.150	0.150	0.159	0.140	0.140	0.140	0.140
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table A.10. Robustness Check: Asymmetric Effects: Expansionary versus Contractionary

This table reports firms' differential debt and equity financing decisions in response to the expansionary or contractionary monetary shocks, separately, in quarter t. Coefficients are estimated from the following regressions.

$$\begin{aligned} y_{i,t} =&\alpha_i + \lambda_{s,q} + \gamma_p \epsilon_t^m(\epsilon_t^m > 0) + \gamma_n \epsilon_t^m(\epsilon_t^m < 0) + \beta_p \epsilon_t^m(\epsilon_t^m > 0) \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \beta_n \epsilon_t^m(\epsilon_t^m < 0) \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta(X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

Columns (1) to (4) report financing decisions on the extensive margin, where the *dependent variable* is a dummy equal to one if the firm chooses bank loans over corporate bonds (panel A) or issues new equity (panel B) in quarter t. Columns (5) to (8) report financing decisions on the intensive margin, where the *dependent variable* is the growth rate of loans (panel A) or equity share (panel B) in quarter t. ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is firm size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	The Extensive Margin				The Intensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Debt Financing	Prob(Borrow from bank)				Δlog(Loan)			
$\epsilon_t^m(\epsilon_t^m > 0)$	0.026***	0.030***	0.028**	0.027***	0.296	0.228	0.208	0.227
	(2.707)	(3.102)	(2.039)	(2.807)	(1.582)	(1.161)	(1.031)	(1.206)
$\epsilon_t^m(\epsilon_t^m < 0)$	0.015***	0.015***	-0.018*	0.022***	0.448***	0.422***	0.297***	0.492***
	(2.765)	(2.611)	(-1.816)	(4.010)	(4.356)	(4.142)	(2.654)	(4.701)
$\epsilon_t^m(\epsilon_t^m > 0) \times$ Size		0.001				-0.086		
		(0.140)				(-0.542)		
$\epsilon_t^m(\epsilon_t^m < 0) \times$ Size		0.012**				0.358***		
		(2.359)				(3.774)		
$\epsilon_t^m(\epsilon_t^m > 0) \times \mathbb{1}$(Invest. Grade)			0.003				0.194	
			(0.144)				(0.378)	
$\epsilon_t^m(\epsilon_t^m < 0) \times \mathbb{1}$(Invest. Grade)			0.051***				0.668***	
			(4.370)				(2.636)	
$\epsilon_t^m(\epsilon_t^m > 0) \times$ D2D				0.002				0.154
				(0.222)				(0.837)
$\epsilon_t^m(\epsilon_t^m < 0) \times$ D2D				0.025***				0.344***
				(3.796)				(3.237)
Observations	11850	11850	11850	11850	184939	184939	184939	184939
R^2	0.396	0.397	0.398	0.397	0.094	0.094	0.094	0.094

	The Extensive Margin				The Intensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Equity Financing	Prob(Net new issuance)				ΔEquity share			
$\epsilon_t^m(\epsilon_t^m > 0)$	0.060	0.023	0.098	-0.024	0.113***	0.078**	0.095**	0.105**
	(0.559)	(0.221)	(0.828)	(-0.202)	(2.646)	(1.989)	(1.975)	(2.473)
$\epsilon_t^m(\epsilon_t^m < 0)$	0.406***	0.428***	0.376***	0.351***	0.149***	0.152***	0.144***	0.104***
	(6.727)	(6.910)	(5.585)	(5.315)	(5.967)	(5.659)	(5.097)	(4.129)
$\epsilon_t^m(\epsilon_t^m > 0) \times$ Size		-0.271**				-0.068		
		(-2.230)				(-1.324)		
$\epsilon_t^m(\epsilon_t^m < 0) \times$ Size		-0.014				-0.059**		
		(-0.225)				(-2.023)		
$\epsilon_t^m(\epsilon_t^m > 0) \times \mathbb{1}$(Invest. Grade)			-0.189				-0.008	
			(-0.763)				(-0.109)	
$\epsilon_t^m(\epsilon_t^m < 0) \times \mathbb{1}$(Invest. Grade)			0.309**				-0.042	
			(2.220)				(-0.950)	
$\epsilon_t^m(\epsilon_t^m > 0) \times$ D2D				-0.030				-0.027
				(-0.256)				(-0.659)
$\epsilon_t^m(\epsilon_t^m < 0) \times$ D2D				0.055				-0.162***
				(0.859)				(-6.187)
Observations	298562	298562	298562	241825	241814	241814	241814	241814
R^2	0.141	0.141	0.141	0.148	0.133	0.133	0.133	0.133
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table A.11. Robustness Check: Firm-Level Borrowing Costs

This table reports the impact of monetary shocks on firm-level borrowing costs (weighted average credit spreads by borrowing amount). Coefficients are estimated from the following regressions.

$$\begin{aligned}Credit\ Spread_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma\epsilon_t^m + \beta\epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta\Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta(X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' W_{i,t-1} + \Gamma_3' Y_{t-1} + \epsilon_{i,t}.\end{aligned}$$

Columns (1) to (4) report the results of loan spreads, which is the difference between the loan rate and the three-month LIBOR. Columns (5) to (8) (columns (9) to (12)) report the results of bond spreads, which is defined as the difference between the offering yield and the three-month LIBOR (maturity-matched interest rate swaps). ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is the firm size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. $W_{i,t-1}$ is a set of debt characteristics including the logarithm of borrowing amount and maturity. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and the inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Loan Spread				Bond Spread (3M LIBOR)				Bond Spread (Swaps)			
ϵ_t^m	0.035***	0.041***	0.033*	0.047***	0.217***	0.227***	0.203***	0.235***	0.095***	0.108***	0.073	0.111***
	(3.467)	(3.965)	(1.851)	(4.537)	(10.375)	(10.602)	(4.150)	(11.176)	(5.382)	(6.108)	(1.629)	(6.457)
$\epsilon_t^m \times$ Size		0.013				0.005				0.003		
		(1.331)				(0.213)				(0.126)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.011				0.005				0.004	
			(0.521)				(-0.031)				(0.095)	
$\epsilon_t^m \times$ D2D				0.031**				0.053**				0.016
				(2.403)				(2.014)				(0.715)
Observations	6525	6525	6525	6525	5370	5370	5279	5370	5409	5409	5317	5409
R^2	0.655	0.655	0.655	0.655	0.616	0.617	0.632	0.618	0.695	0.697	0.718	0.697
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A.12. Robustness Check: Other (Real) Effects

This table reports the impact of monetary shocks on firm-level trade credit, cash holding, dividend payout (dummy), and stock excess return. Coefficients are estimated from the following regressions.

$$\begin{aligned} y_{i,t} =& \alpha_i + \lambda_{s,q} + \gamma \epsilon_t^m + \beta \epsilon_t^m \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \eta \Delta GDP_t \times (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) \\ &+ \delta (X_{i,t-1} - \mathrm{E}_i(X_{i,t})) + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_{t-1} + \epsilon_{i,t}. \end{aligned}$$

ϵ_t^m is the monetary shock, and $X_{i,t-1}$ is the firm size, credit rating or distance to default (D2D) in the previous quarter. $Z_{i,t-1}$ is a set of additional firm control variables, including market-to-book ratio, liquidity, tangibility, leverage, and a dummy for dividend payout. Y_{t-1} is a set of macroeconomic variables including four lags of GDP growth and inflation rate. Monetary shocks and firm control variables are standardized. The sample covers periods from 1990Q2 to 2018Q4 (excluding the financial crisis from 2008Q3 to 2009Q2). The firm and sector-quarter fixed effects are indicated in the table. Standard errors are heteroskedasticity-robust and clustered at the firm level, and t-statistics are in parentheses. All firm-level variables are winsorized at the 1% level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Trade Credit				Cash Holding		
ϵ_t^m	-0.054**	-0.042*	-0.054**	-0.027	0.043*	0.058**	0.039	0.058**
	(-2.298)	(-1.718)	(-1.965)	(-1.195)	(1.645)	(2.171)	(1.325)	(2.117)
$\epsilon_t^m \times$ Size		0.045*				0.130***		
		(1.743)				(4.893)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			0.092***				0.148***	
			(2.793)				(2.585)	
$\epsilon_t^m \times$ D2D				0.087***				-0.029
				(3.871)				(-1.085)
Observations	241825	241825	241825	241825	241825	241825	241825	241825
R^2	0.648	0.648	0.648	0.648	0.795	0.795	0.795	0.795
		Dividend Payout (Dummy)				Stock Excess Return		
ϵ_t^m	-0.205***	-0.259***	-0.175**	-0.265***	-1.347***	-1.585***	-1.643***	-1.570***
	(-2.839)	(-3.451)	(-2.202)	(-3.567)	(-19.288)	(-22.222)	(-20.775)	(-22.962)
$\epsilon_t^m \times$ Size		-0.269***				0.165**		
		(-3.121)				(2.329)		
$\epsilon_t^m \times \mathbb{1}$(Invest. Grade)			-0.595***				0.416***	
			(-2.673)				(3.190)	
$\epsilon_t^m \times$ D2D				-0.007				0.024
				(-0.093)				(0.346)
Observations	241825	241825	241825	241825	240879	240879	240879	240879
R^2	0.559	0.560	0.559	0.559	0.134	0.137	0.137	0.137
Firm & Aggregate controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Appendix B

Chapter Two Appendix

B.1 Details on Data and Sample Construction

Below are details of how we construct aggregate and firm-level variables, how we identify lead lenders for each loan origination, and the filters we apply to obtain our final sample.

B.1.1 Aggregate Variables Construction

The aggregate sample for aggregate time series regressions contains annual data from 1961 to 2019. Financial sector labor share is the ratio of compensation of employees to net value added of the financial business sector from Integrated Macroeconomic Accounts (IMA); while aggregate labor share is the ratio of aggregate compensation of employees to GDP. We apply one-sided HP filter to remove the trend of the aggregate labor share. Wage growth is the growth rate in the real wages and salaries per full-time equivalent employee from NIPA Table 6.6, deflated by the Consumer Price Index for All Urban Consumers from FRED. Market return and risk-free rate are from Kenneth French's data library. Debt growth is the growth rate of credit market instrument liabilities (sum of real debt and loans) for non-financial business sector from the Flow of Funds Table L.103. Non-financial business sector leverage is defined as the ratio of its liabilities to corporate equity. Similarly, we obtain debt growth and leverage ratio for financial business sector using debt, loans and equity data from IMA. Aggregate investment growth is the growth rate of fixed investment from NIPA Table 1.1.5. Value added growth is the growth rate of the real net value added for non-financial corporate sector from IMA. The credit spread is the Moody's Baa corporate bond yield in excess of Aaa corporate bond yield from the Federal Reserve. Term Spread is 10-year Treasury rate minus 1-year Treasury rate. The 3-month T-bill rate, corporate bond yield and Treasury rate are from St. Louis Fed. The price-dividend (PD) ratio is obtained from Shiller's webpage. We get the leverage ratio of AEM and HKM directly from Asaf Manela's website. We then take the simple average to obtain the annual observations.

Table B.1 below describes the definition and sources of the main variables.

Labor Skill Measure

Our benchmark analysis uses the Specific Vocational Preparation (SVP) data from the 1991 Dictionary of Occupational Titles (DOT)[1], available from the Department of Labor, and employee data from the Bureau of

[1] Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 from U.S. Department of Labor. The data for 1991 DOT are obtained from the Inter-university Consortium for Political and Social Research (ICPSR) Study No

Labor Statistics (BLS), Occupational Employment Statistics (OES) program. For each occupation defined in the DOT, it provides information about the Specific Vocational Preparation (SVP) level of the occupation. The SVP measures the amount of time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. SVP takes value from 1 to 9, where SVP = 1 corresponds to the lowest level of preparation and SVP = 9 corresponds to the highest level of preparation. We define high skill occupations to be those that have are associated with a SVP equal to or greater than 7 (over 2 years of preparation).[2] The total wage payment of high skill workers are computed as the product of total employment and average annual wage rate. The labor share of high skill workers ("HSLS") is defined as the ratio of total wage payment of high skill workers to GDP for the aggregate economy. The labor share of high skill workers in the finance industry ("HSFLS") is defined as the total wage payment of high skill workers to the net value added of finance industry. The aggregate high skill workers labor share has a mean of 0.2 and a standard deviation of 0.03. The high skill workers labor share in the finance industry has a mean of 0.142 and a standard deviation of 0.015. The correlation between HSFLS and FLS is around 0.62 and the correlation between HSFLS and HSLS is around 0.08.

B.1.2 Distance to Default (D2D)

Following Merton (1974) and Gilchrist and Zakrajšek (2012), the distance to default is defined as

$$D2D = \frac{log(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}, \tag{B.1}$$

where V is the total value of firm, μ_V is the annual expected return on V, σ_V is the annual volatility of the firm's value, and D is firm's debt. Firm value V is estimated following an iterative procedure,

1. Set an initial value for the firm value equal to the sum of firm debt and equity: $V = E + D$, where $E = \text{PRC} \times \text{SHROUT}$ (daily stock price times the number of shares outstanding from CRSP).
2. Estimate μ_V and σ_V over a 250-day moving window. The return on firm value is defined as the daily log return on assets, $\Delta logV$.
3. Get a new estimate of V for every day of the 250-day moving window based on the Black-Scholes-Merton option-pricing framework

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2), \tag{B.2}$$

   where $\delta_1 = \frac{log(V/D)+(r+0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}}$ and $\delta_2 = \delta_1 - \sigma_V\sqrt{T}$ where r is the daily one-year constant maturity Treasury-yield from St. Louis Fed.
4. Iterate on steps 2 and 3 until convergence.

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[2]The following is the detailed explanation of SVP index: 1. Short demonstration only; 2. Anything beyond short demonstration up to and including 1 month; 3. 1 month < preparation time ≤ 3 months; 4. 3 month < preparation time ≤ 6 months; 5. 6 month < preparation time ≤ 1 year; 6. 1 year < preparation time ≤ 2 year; 7. 2 year < preparation time ≤ 4 year; 8. 4 year < preparation time ≤ 10 year; 9. over 10 years.

B.1.3 Identifying Lead Lenders

We use Dealscan, which contains origination information on both sole-lender loans and syndicated loans, to determine relationships between firms and banks. There are two variables in Dealscan that are useful in determining the lead agent: a text variable "LenderRole" that defines the lender role and a Yes/No lead arranger credit variable "LeadArrangerCredit". In the case of syndicated loans with multiple lenders, we follow lender's ranking hierarchy proposed by Chakraborty, Goldstein and MacKinlay (2018) to identify the lead lender for each loan:

1. LenderRole == "Admin Agent"
2. LenderRole == "Lead Bank"
3. LenderRole == "Lead Arranger"
4. LenderRole == "Mandated Lead Arranger"
5. LenderRole == "Mandated Arranger"
6. LenderRole == "Arranger" or "Agent" and LeadArrangerCredit == "Yes"
7. LenderRole == "Arranger" or "Agent" and LeadArrangerCredit == "No"
8. LenderRole is defined as other than those previously listed ("Participant" and "Secondary investor" are also excluded) and LeadArrangerCredit == "Yes"
9. LenderRole is defined as other than those previously listed ("Participant" and "Secondary investor" are also excluded) and LeadArrangerCredit == "No"
10. LenderRole == "Participant" or "Secondary investor"

For a given loan package, the lender with the highest title (following our ten-part hierarchy) is considered as the lead agent. About 81% of the matched facility in our sample has only one lead lender. About 76% of the matched facilities in our sample have a single lead lender that fall under one of the first six categories. Any loan where a single lead agent cannot be determined is excluded from the sample. To determine each lender's loan amount, we do the following: for those loans which have allocation information, we use the provided data (FacilityAmt $\times$ BankAllocation) . For those loans without allocation data, we estimate the average allotment given the lender's position in the syndicate and the syndicate size. Specifically, we estimate the missing values for "BankAllocation" in a Tobit regression where we include number of lenders, number of lead agents, lenders' ranking, loan amount and an indicator for lead agent.

B.1.4 Sample Selection

Compustat We apply the following filters to our Compustat firms sample:

- We drop firms in finance, insurance, and real estate sectors (SIC $\in$ [6000, 6799]), utilities (SIC $\in$ [4900, 4999]) and public administration (SIC $\in$ [9000, 9999]).
- We drop firms with negative or missing sales or assets, and negative cash.

FR Y-9C We apply the following filters to our bank holding company (BHC) sample:

- We drop observations with missing or negative total assets (BHCK2170)
- We keep bank holding companies (RSSD9331==28)
- We drop lower-tier holding companies whose higher-tier also files Y-9C (BHCK9802==2)
- We keep holding company (RSSD9048 ==500) and exclude securities broker or dealer (RSSD9048 ==700), insurance broker or company (RSSD9048 ==550), utility company (RSSD9048 ==710), and other non-depository institution (RSSD9048 ==720) but keep Goldman Sachs, Morgan Stanley, Ally and American Express.

- We drop observations with negative labor share and interest expense.

Dealscan We apply the following filters to our Dealscan sample:

- We keep facilities measured in U.S Dollars. (Currency==“United States Dollars”)
- We keep facilities with borrowers and lenders in USA. (Country==“USA”)
- We keep facilities with borrowers that are corporations. (InstitutionType==“Corporation”)
- We keep facilities with lenders that are U.S banks. (InstitutionType ==“US Bank”)
- We keep facilities that are either sole-lender loans or syndicated loans. (DistributionMethod ==“Syndication” or DistributionMethod ==“Sole Lender”)
- We keep facilities with single lead agent belongs to the first six categories listed above.
- We only keep holding companies that have issued at least 50 facilities in our merged sample.
- We keep firms that have at least three observations in the sample.

Loan pricing We apply the following filters to our loan pricing sample:

- We drop facilities with negative loan spread (“All-in-Drawn”) or facilities with loan spread over 1000 basis points.
- We drop facilities with maturity less than one year.

Table B.1. Variable Definitions

Definition	Variable Definitions	Data sources
Bank Characteristics		
Labor share	Labor expense over sum of labor expense and earning $\text{FLS} = \frac{\text{XLR}}{\text{XLR+EBITDA}}$	FR Y-9C
Size	Log of total book assets (BHCK2170)	FR Y-9C
ROA	Net income (BHCK4340) divided by total assets (BHCK2170)	FR Y-9C
Interest Expense	Total interest expense (BHCK4073) divided by total deposits (sum of BHDM6631, BHDM6636, BHFN6631, and BHFN6636)	FR Y-9C
Capital ratio	Total equity (BHCK3210) divided by total assets (BHCK2170)	FR Y-9C
Non-performing Loan	Sum of BHCK5525, BHCK5524, BHCK5526 and BHCK4635, divided by total loan	FR Y-9C
Loan growth	$\Delta\text{Loan}_t = \frac{\text{Loan}_t - \text{Loan}_{t-1}}{0.5(\text{Loan}_t + \text{Loan}_{t-1})}$	FR Y-9C
Earnings growth	$\Delta Earning_t = \frac{EBIT_t - EBIT_{t-1}}{0.5*(EBIT_t + EBIT_{t-1})}$	FR Y-9C
Total Loan	Sum of BHCK2122 and BHCK2123	FR Y-9C
Business Loan	BHCK1766 (Commercial & Industrial Loan)	FR Y-9C
Business Loan (U.S)	BHCK1763	FR Y-9C
Real Estate Loan	BHCK1410	FR Y-9C
Consumer Loan	BHCK1975	FR Y-9C
Data Processing Fees	BHCKC017	FR Y-9C
Legal expense	BHCK4141	FR Y-9C
Firm Characteristics		
Investment rate	Capital expenditure (CAPX) over lagged PPENT	Compustat
Earnings growth	$\Delta\text{Earnings}_t = \frac{\text{IB}_t - \text{IB}_{t-1}}{0.5(\text{IB}_t + \text{IB}_{t-1})}$	Compustat
Firm size	Log of total assets (AT)	Compustat
Financial leverage	Sum of short-term and long-term debt (DLC + DLTT), divided by total assets	Compustat
Cash	Cash and short-term investment (CHE), divided by total assets	Compustat
Tobin's Q	$\frac{\text{AT+CSHOxPRCC}_F - \text{CEQ}}{\text{AT}}$	Compustat
Credit rating	S&P long-term SPLTICRM	Compustat
Sales growth	$\Delta\text{Sales}_t = \frac{\text{Sales}_t - \text{Sales}_{t-1}}{0.5(\text{Sales}_t + \text{Sales}_{t-1})}$	Compustat
Tangibility	$(0.715 \times \text{RECT} + 0.547 \times \text{INVT} + 0.535 \times \text{PPENT})/\text{AT}$	Compustat
Excess return	RET − risk-free rate	CRSP
Whited-Wu index	WW Index = 0.65 - 0.091 CF - 0.062DIVPOS + 0.021TLTD - 0.044LNTA + 0.102ISG - 0.035SG.	Hennessy and Whited (2007)
Aggregate variables		
Financial sector labor share	Compensation of employees divided by net value added	IMA/NIPA
Aggregate labor share	Compensation of employees divided by GDP	NIPA
Wage growth	Growth rate of the real wages and salaries per full-time equivalent employee	NIPA
CPI	Consumer Price Index for All Urban Consumers	FRED
Debt growth	Growth rate of credit market instrument liabilities (sum of real debt and loans) for non-financial business sector	Flow of Funds
	Growth rate of credit market instrument liabilities (sum of real debt and loans) for financial business sector	IMA
Investment growth	Growth rate of nonresidential fixed investment	NIPA
GDP growth	Growth rate of real GDP	NIPA
Value added growth	Growth rate of real net value added	IMA
Credit spread	Moody's Baa corporate bond yield in excess of Fed Funds rate	St. Louis Fed
Term spread	10-year Treasury rate minus 1-year Treasury rate	St. Louis Fed
PD	price-dividend (PD) ratio	Shiller's webpage
Financial leverage	FI financial leverage (AEM and HKM)	Asaf Manela's website
Market excess return	Market return and risk-free rate	Kenneth French

B.2 Additional Empirical Results

This section provides additional empirical results, we summarize them here, although all are mentioned in the main text. Table B.2 shows the relationship between FLS and debt growth in the financial sector, it is analogous to Table 2.3 which does this for aggregate debt growth. Tables B.3, B.4, and B.5 provide multivariate results relating FLS and various controls to aggregate equity returns, debt growth, cost of credit, GDP growth, and investment growth; they are analogous to Tables 2.2, 2.3, 2.4, 2.5, and 2.6. Table B.6 recomputes the main aggregate results with the labor share of high skilled workers as a control; it is analogous to Tables 2.2, 2.3, 2.4, 2.5, and 2.6. Tables B.7, B.8, B.9, B.10, B.11, and B.12 recompute the main aggregate results replacing FLS by the financial sector's labor to capital ratio is the key independent variable; they are also analogous to Tables 2.2, 2.3, 2.4, 2.5, 2.6, and B.2. Table B.13 provides summary statistics for the firm level results. Table B.14 relates bank level FLS to bank level loan growth and is similar to Table 2.7, but it breaks down loans by type. Table B.15 relates bank level FLS to real firm level outcomes and is similar to Table 2.10 but it separates firms into constrained and unconstrained. Figure B.2 uses a scatterplot to highlight the negative relationship between output and the financial sector employment as a share of total employment.

In B.16, we report the correlation between two extracted FLS shocks: ϵ_1 and ϵ_2, and other key variables, including FLS, ν_b, and $\frac{N_b}{N}$. To obtain ϵ_1, we regress FLS on TFP growth, changes in credit spread, changes in term spread, macro uncertainty, and financial uncertainty using an expanding window and extract the residuals. To obtain ϵ_2, we estimate a VAR(1) that includes FLS, GDP growth, wage growth, aggregate labor share, term spread, the price-to-dividend ratio, credit spread, and HKM, and extract the residuals to FLS. The sample for these two exercises is from 1970 to 2019 since HKM has been available since 1970. The impulse responses are shown in figure B.8.

Table B.17 provides direct evidence for one specific source of FLN shocks. For example, a higher regulation burden raises the banks' legal and data processing expenses. A bank that has increasing legal and data processing expenses also has a higher FLS, a lower growth rate of loan lending, and a higher interest rate charged from its borrowers.

Figure B.1. Number of Bank Holding Companies

This figure plots the number of bank holding companies from FR Y-9C in our sample every year from 1986 to 2019. The number of bank holding companies increase from 1,321 in year 1986 to 2,204 in year 2005. The number of bank holding companies drops dramatically after 2005 to 304 in year 2019.

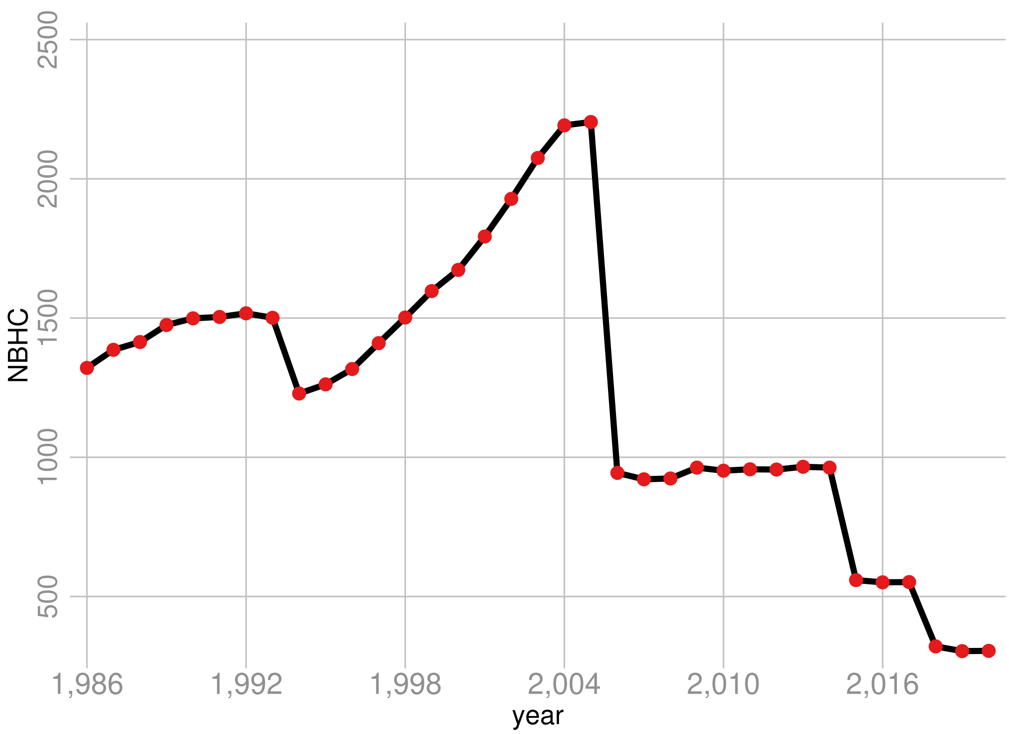


Table B.2. Aggregate FLS and financial sector debt growth

This table reports the results of aggregate-level annual time-series contemporaneous (t), 1-year ahead ($t+1$), 3-year ahead ($t+3$), and 5-year ahead ($t+5$) predictability of financial sector debt growth by financial sector labor share at t (FLS). The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	PD	ΔFVA	HKM	AEM
Panel A: Contemporaneous effect on debt growth, financial sector										
FLS	-0.27	-0.27	-0.05	-0.21	-0.20	-0.08	-0.26	-0.33	-0.15	-0.24
t	-1.93	-1.89	-0.37	-1.45	-1.51	-0.50	-1.89	-1.21	-0.92	-2.25
Control		0.20	1.66	1.22	-0.05	-0.03	0.00	-0.08	0.00	0.00
t		0.20	3.81	3.46	-1.45	-1.78	-0.45	-0.40	-1.93	-0.24
R2	0.02	0.01	0.28	0.07	0.09	0.15	0.01	0.01	0.13	0.01
Panel B: Predicting debt growth, financial sector, 1-year ahead										
FLS	-0.50	-0.50	-0.30	-0.42	-0.48	-0.49	-0.49	-0.40	-0.40	-0.43
t	-2.76	-2.74	-1.85	-2.25	-2.99	-2.53	-2.72	-1.55	-2.20	-3.50
Control		-0.99	1.52	1.85	-1.70	-0.15	-0.06	0.14	-0.26	-0.07
t		-1.08	3.94	3.42	-0.58	-0.08	-1.29	0.78	-1.98	-0.97
R2	0.13	0.13	0.34	0.26	0.12	0.11	0.14	0.12	0.21	0.12
Panel C: Predicting debt growth, financial sector, 3-year ahead										
FLS	-1.47	-1.47	-1.17	-1.36	-1.45	-1.36	-1.41	-1.42	-1.23	-0.95
t	-3.59	-3.41	-2.58	-3.26	-3.39	-2.81	-4.47	-2.11	-2.53	-3.61
Control		-0.37	2.18	2.46	-1.91	-1.62	-0.45	0.07	-0.61	-0.47
t		-0.12	1.73	2.45	-0.18	-0.38	-1.95	0.14	-1.38	-2.23
R2	0.14	0.13	0.19	0.16	0.13	0.13	0.26	0.13	0.19	0.19
Panel D: Predicting debt growth, financial sector, 5-year ahead										
FLS	-2.48	-2.63	-2.16	-2.38	-2.47	-1.92	-2.30	-2.57	-2.12	-1.05
t	-3.24	-3.10	-2.61	-3.21	-3.04	-2.96	-4.78	-1.99	-2.37	-1.78
Control		7.70	2.16	2.16	-1.23	-7.45	-0.89	-0.11	-0.87	-1.34
t		1.38	0.86	0.78	-0.06	-1.44	-2.52	-0.13	-0.97	-3.81
R2	0.14	0.17	0.15	0.14	0.13	0.18	0.32	0.13	0.18	0.33

Table B.3. FLS and excess equity return, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting stock market excess return at $t+k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	ΔWage	ΔGDP	LS	TS	PD	ΔFVA	CS	HKM	R^2
$k=1$	0.28	-1.98	-0.77	1.61	0.04	-0.24	0.43	-0.03	0.00	0.00
t	0.84	-0.57	-0.51	0.32	1.70	-3.32	1.45	-0.34	0.11	
$k=3$	1.34	-8.18	-0.29	4.11	0.14	-0.49	0.72	-0.18	0.00	0.26
t	1.76	-1.91	-0.21	0.37	2.91	-2.22	1.19	-1.40	0.28	
$k=5$	5.06	-17.41	2.87	6.03	0.17	-0.61	2.06	0.03	0.00	0.53
t	6.02	-4.00	1.84	0.48	6.03	-2.57	2.76	0.22	0.55	

Table B.4. FLS and credit markets, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting debt growth or credit risk (measured by the Baa-FedFunds spread) at $t+k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	ΔWage	ΔGDP	LS	TS	PD	ΔFVA	CS	HKM	R^2
Panel A: Debt growth										
$k=1$	-0.61	1.41	0.71	-1.67	0.00	-0.05	-0.15	0.00	0.00	0.41
t	-3.30	1.54	1.58	-0.84	0.40	-1.27	-1.08	0.01	-0.67	
$k=3$	-1.84	-0.85	0.18	0.72	0.07	-0.38	-0.27	0.11	-0.01	0.45
t	-4.73	-0.45	0.15	0.14	3.95	-6.80	-0.79	0.97	-4.96	
$k=5$	-2.83	-4.71	0.28	10.62	0.11	-0.64	-0.62	0.14	-0.02	0.48
t	-3.97	-2.16	0.16	1.11	3.23	-5.02	-1.51	1.17	-12.29	
Panel B: Credit risk										
$k=1$	0.01	-0.04	-0.23	0.25	0.01	0.02	-0.02	0.01	0.00	0.56
t	0.54	-0.21	-1.79	0.80	8.19	4.36	-0.79	2.19	-0.47	
$k=3$	0.14	-0.19	0.04	0.09	-0.01	0.08	0.06	0.02	0.00	0.39
t	3.47	-1.11	0.46	0.27	-3.60	6.53	3.05	2.04	1.12	
$k=5$	0.08	0.49	-0.03	-0.42	0.00	0.05	0.03	0.00	0.00	0.19
t	2.35	1.78	-0.25	-0.36	-2.18	5.64	1.74	-0.59	4.28	

Table B.5. FLS and real quantities, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting GDP growth and Investment growth at $t+k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	ΔWage	ΔGDP	LS	TS	PD	ΔFVA	CS	HKM	R^2
Panel A: GDP growth										
$k=1$	-0.08	0.47	-0.10	-0.29	0.01	-0.04	0.04	0.01	0.00	0.46
	-2.21	1.44	-0.49	-0.93	3.65	-3.13	1.20	1.18	-3.84	
$k=3$	-0.26	0.29	-0.67	-0.16	0.02	-0.15	-0.06	0.04	-0.01	0.42
	-2.20	0.43	-1.59	-0.16	2.81	-4.40	-0.55	0.97	-4.14	
$k=5$	-0.26	-0.45	-0.54	1.27	0.02	-0.19	-0.04	0.04	-0.01	0.35
	-1.36	-0.48	-1.17	0.70	1.76	-3.23	-0.34	0.88	-4.61	
Panel B: Investment growth										
$k=1$	-0.45	1.39	-0.26	-1.37	0.03	-0.09	0.06	-0.03	0.00	0.50
	-3.17	1.73	-0.53	-1.94	4.58	-2.47	0.56	-1.48	-0.59	
$k=3$	-0.88	0.03	-2.71	-1.72	0.08	-0.39	0.06	0.01	-0.01	0.41
	-3.01	0.02	-2.52	-0.48	3.17	-3.96	0.22	0.18	-3.92	
$k=5$	-0.21	-1.95	-2.98	0.50	0.07	-0.46	0.30	-0.02	-0.01	0.24
	-0.49	-1.40	-2.39	0.08	1.86	-3.54	1.42	-0.29	-4.37	

Table B.6. High skilled labor share as a placebo

This table reports the results of aggregate-level annual time-series 1-year ahead ($t+1$) predictability of various variables of interest by high skilled labor share (HSLS) or by financial sector labor share (FLS) at t. The variables of interest are the market premium ($R^m - R^f$), debt growth (ΔDebt), Baa minus Fed Funds credit spread (CrSpr), investment growth (ΔInv) and GDP growth (ΔGDP) in columns 1-5. The top panel presents univariate results with just HSLS, the bottom panel presents bivariate results with HSLS and FLS. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1997 to 2019. All the variables are real.

	$R^m - R^f$	ΔDebt	CrSpr	ΔInv	ΔGDP
Panel A: Univariate					
HSLS	-0.21	-0.55	25.95	-1.69	-0.17
t	-0.10	-0.31	0.61	-0.98	-0.53
R^2	-0.05	-0.04	-0.01	-0.02	-0.03
Panel B: Bivariate					
HSLS	-1.44	1.87	-26.66	1.76	0.42
t	-0.61	1.89	-0.92	2.17	4.99
FLS	0.004	-0.008	0.17	-0.011	-0.002
t	1.40	-4.93	4.34	-8.50	-12.33
R^2	-0.09	0.36	0.28	0.20	0.39

Table B.7. Financial labor to total assets ratio and excess equity return

This table reports the results of aggregate-level regressions of stock market excess return at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous (k = 0), 1-year (k = 1), 3-year (k = 3), and 5-year (k = 5) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
ν_b	-0.16	-0.19	-0.12	0.09	-0.16	-1.02	-0.20	0.07	-0.19	0.55
t	-0.44	-0.42	-0.30	0.22	-0.48	-2.02	-0.65	0.25	-0.37	0.95
Control		-2.12	0.17	2.33	0.00	0.06	0.02	0.84	0.00	0.00
t		-1.45	0.21	2.12	-0.05	2.37	0.22	3.20	-1.81	-1.96
R^2	-0.02	-0.02	-0.03	0.00	-0.03	0.05	-0.03	0.08	-0.03	0.03
Panel B: 1-year ahead										
ν_b	1.15	1.14	0.97	0.97	1.09	0.97	1.81	1.22	1.25	0.55
t	3.46	3.20	3.75	3.16	3.39	2.04	2.92	3.78	3.82	0.95
Control		-1.09	-0.74	-1.69	0.05	0.01	-0.37	0.21	0.01	0.00
t		-0.54	-0.75	-1.41	1.72	0.75	-3.39	1.39	3.18	-1.96
R^2	0.04	0.03	0.03	0.05	0.04	0.03	0.14	0.03	0.09	0.03
Panel C: 3-years ahead										
ν_b	3.28	3.25	3.04	2.76	3.24	2.31	4.66	3.26	4.23	4.32
t	4.23	3.96	4.05	3.75	3.92	1.65	4.43	4.09	5.30	3.70
Control		-4.50	-0.92	-4.84	0.03	0.06	-0.79	-0.08	0.02	-0.01
t		-0.72	-0.71	-1.80	0.40	1.18	-3.08	-0.27	2.86	-2.01
R^2	0.13	0.14	0.12	0.17	0.12	0.15	0.26	0.12	0.28	0.17
Panel D: 5-years ahead										
ν_b	6.35	6.26	5.39	5.07	5.96	4.63	9.19	6.14	7.46	7.64
t	3.71	3.61	2.55	3.10	2.91	2.69	8.21	3.57	5.95	3.78
Control		-8.37	-3.71	-11.77	0.32	0.11	-1.65	-0.70	0.05	-0.03
t		-0.85	-1.26	-2.71	2.62	1.88	-6.45	-1.50	4.52	-4.70
R^2	0.19	0.20	0.20	0.29	0.24	0.22	0.40	0.19	0.46	0.30

Table B.8. Financial labor to total assets ratio and non-financial corporate sector debt growth

This table reports the results of aggregate-level regressions of non-financial corporate debt growth at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
ν_b	-1.12	-1.11	-0.75	-1.00	-1.03	-0.87	-1.25	-1.14	-1.16	-1.20
t	-4.45	-4.84	-3.39	-3.48	-4.88	-4.66	-4.57	-4.03	-4.00	-3.20
Control		0.81	1.43	1.08	-0.06	-0.02	0.07	-0.08	0.00	0.00
t		0.97	9.61	2.10	-2.89	-1.44	1.31	-0.67	-3.94	1.64
R^2	0.30	0.30	0.47	0.33	0.42	0.33	0.31	0.29	0.36	0.26
Panel B: 1-year ahead										
ν_b	-1.04	-1.05	-0.69	-0.85	-0.98	-1.32	-1.21	-0.96	-1.04	-0.86
t	-5.22	-4.79	-3.17	-3.83	-4.92	-8.89	-5.85	-4.43	-4.60	-4.14
Control		-0.96	1.35	1.79	-0.04	0.02	0.09	0.26	-0.01	0.00
t		-0.76	2.88	2.80	-1.29	1.87	1.96	3.16	-3.82	-0.38
R^2	0.26	0.26	0.40	0.37	0.30	0.29	0.28	0.31	0.34	0.16
Panel C: 3-years ahead										
ν_b	-1.93	-1.94	-1.61	-1.68	-1.91	-2.88	-1.91	-1.76	-1.60	-1.29
t	-2.68	-2.73	-1.89	-2.53	-2.57	-4.10	-2.38	-2.40	-2.03	-1.09
Control		-1.90	1.23	2.30	-0.01	0.06	-0.01	0.59	0.00	0.00
t		-0.45	0.99	2.46	-0.20	3.13	-0.13	4.19	-1.70	-0.73
R^2	0.17	0.16	0.17	0.19	0.15	0.26	0.15	0.21	0.09	0.10
Panel D: 5-years ahead										
ν_b	-2.43	-2.42	-2.28	-2.30	-2.40	-3.33	-2.15	-2.28	-0.99	-0.43
t	-1.98	-1.98	-1.66	-2.00	-1.96	-2.67	-1.52	-1.86	-0.76	-0.21
Control		0.20	0.56	1.15	-0.02	0.06	-0.16	0.48	0.00	0.00
t		0.03	0.38	0.56	-0.22	1.34	-1.23	2.34	0.60	-0.46
R^2	0.14	0.12	0.12	0.13	0.12	0.17	0.13	0.14	0.00	-0.03

Table B.9. Financial labor to total assets ratio and Baa - Fed Funds spread

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
v_b	0.27	0.26	0.29	0.31	0.25	0.00	0.25	0.27	0.23	0.23
t	3.66	4.13	4.29	4.91	4.87	0.09	3.05	3.96	2.67	2.20
Control		-0.41	0.11	0.43	0.01	0.02	0.01	0.02	0.00	0.00
t		-1.53	1.09	2.71	2.88	12.79	0.53	0.88	-0.21	0.82
R^2	0.26	0.28	0.26	0.35	0.31	0.90	0.25	0.25	0.17	0.20
Panel B: 1-year ahead										
v_b	0.28	0.28	0.22	0.28	0.25	0.15	0.26	0.26	0.22	0.17
t	4.02	3.92	4.32	4.81	6.82	2.29	3.71	3.92	3.18	3.05
Control		0.02	-0.24	0.05	0.02	0.01	0.01	-0.04	0.00	0.00
t		0.07	-1.75	0.31	7.02	5.66	1.00	-1.92	0.58	3.25
R^2	0.27	0.26	0.33	0.26	0.40	0.41	0.27	0.29	0.14	0.20
Panel C: 3-years ahead										
v_b	0.19	0.19	0.14	0.17	0.18	0.29	0.13	0.18	0.16	0.09
t	3.01	3.05	2.38	3.04	3.68	4.44	1.84	2.74	2.05	0.94
Control		0.29	-0.19	-0.15	0.01	-0.01	0.03	-0.03	0.00	0.00
t		1.12	-2.81	-1.53	2.18	-2.47	2.46	-1.79	0.48	1.80
R^2	0.11	0.12	0.14	0.11	0.13	0.19	0.17	0.11	0.05	0.09
Panel D: 5-years ahead										
v_b	0.16	0.16	0.16	0.17	0.15	0.18	0.11	0.16	0.04	-0.04
t	1.80	1.82	1.80	2.12	1.92	2.22	1.26	1.92	0.44	-0.57
Control		0.01	0.01	0.14	0.00	0.00	0.03	0.01	0.00	0.00
t		0.02	0.10	0.74	0.94	-0.72	1.95	0.31	-1.51	2.14
R^2	0.08	0.06	0.06	0.07	0.07	0.07	0.10	0.06	-0.01	0.04

Table B.10. Financial labor to total assets ratio and GDP growth

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
v_b	-0.25	-0.26		-0.16	-0.22	-0.34	-0.31	-0.23	-0.17	-0.13
t	-3.35	-3.10		-3.09	-6.16	-4.89	-3.64	-2.57	-3.84	-2.91
Control		-0.47		0.86	-0.03	0.01	0.03	0.09	0.00	0.00
t		-2.29		6.22	-6.28	1.53	1.96	1.68	-5.19	-0.43
R^2	0.15	0.17		0.42	0.36	0.18	0.18	0.21	0.24	0.01
Panel B: 1-year ahead										
v_b	-0.21	-0.22	-0.14	-0.13	-0.21	-0.44	-0.23	-0.18	-0.15	-0.09
t	-2.61	-2.62	-1.93	-2.73	-2.83	-4.75	-2.67	-2.07	-3.04	-1.10
Control		-0.35	0.28	0.75	0.00	0.01	0.01	0.11	0.00	0.00
t		-3.36	4.79	4.29	-0.77	3.26	0.75	4.44	-3.72	-0.66
R^2	0.10	0.10	0.15	0.30	0.09	0.41	0.09	0.19	0.09	0.01
Panel C: 3-years ahead										
v_b	-0.46	-0.46	-0.47	-0.37	-0.46	-0.76	-0.43	-0.44	-0.21	-0.10
t	-1.88	-1.88	-2.01	-1.96	-1.97	-3.04	-1.68	-1.75	-1.33	-0.41
Control		-0.06	-0.04	0.86	0.00	0.02	-0.02	0.07	0.00	0.00
t		-0.11	-0.14	2.19	0.05	3.60	-0.38	1.47	-1.31	-0.95
R^2	0.09	0.07	0.07	0.14	0.07	0.20	0.08	0.08	-0.01	0.00
Panel D: 5-years ahead										
v_b	-0.65	-0.64	-0.68	-0.57	-0.64	-0.84	-0.60	-0.64	-0.10	0.02
t	-1.70	-1.72	-1.88	-1.87	-1.83	-1.83	-1.50	-1.64	-0.62	0.09
Control		1.19	-0.13	0.72	-0.01	0.01	-0.03	0.05	0.00	0.00
t		1.16	-0.50	1.31	-0.41	1.65	-0.49	0.74	0.11	-0.66
R^2	0.12	0.12	0.10	0.12	0.10	0.13	0.10	0.10	-0.04	-0.03

Table B.11. Financial labor to total assets ratio and Investment growth

This table reports the results of aggregate-level regressions of Investment growth at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
ν_b	-0.25	-0.26		-0.16	-0.22	-0.34	-0.31	-0.23	-0.17	-0.13
t	-3.35	-3.10		-3.09	-6.16	-4.89	-3.64	-2.57	-3.84	-2.91
Control		-0.47		0.86	-0.03	0.01	0.03	0.09	0.00	0.00
t		-2.29		6.22	-6.28	1.53	1.96	1.68	-5.19	-0.43
R^2	0.15	0.17		0.42	0.36	0.18	0.18	0.21	0.24	0.01
Panel B: 1-year ahead										
ν_b	-0.21	-0.22	-0.14	-0.13	-0.21	-0.44	-0.23	-0.18	-0.15	-0.09
t	-2.61	-2.62	-1.93	-2.73	-2.83	-4.75	-2.67	-2.07	-3.04	-1.10
Control		-0.35	0.28	0.75	0.00	0.01	0.01	0.11	0.00	0.00
t		-3.36	4.79	4.29	-0.77	3.26	0.75	4.44	-3.72	-0.66
R^2	0.10	0.10	0.15	0.30	0.09	0.41	0.09	0.19	0.09	0.01
Panel C: 3-years ahead										
ν_b	-0.46	-0.46	-0.47	-0.37	-0.46	-0.76	-0.43	-0.44	-0.21	-0.10
t	-1.88	-1.88	-2.01	-1.96	-1.97	-3.04	-1.68	-1.75	-1.33	-0.41
Control		-0.06	-0.04	0.86	0.00	0.02	-0.02	0.07	0.00	0.00
t		-0.11	-0.14	2.19	0.05	3.60	-0.38	1.47	-1.31	-0.95
R^2	0.09	0.07	0.07	0.14	0.07	0.20	0.08	0.08	-0.01	0.00
Panel D: 5-years ahead										
ν_b	-0.65	-0.64	-0.68	-0.57	-0.64	-0.84	-0.60	-0.64	-0.10	0.02
t	-1.70	-1.72	-1.88	-1.87	-1.83	-1.83	-1.50	-1.64	-0.62	0.09
Control		1.19	-0.13	0.72	-0.01	0.01	-0.03	0.05	0.00	0.00
t		1.16	-0.50	1.31	-0.41	1.65	-0.49	0.74	0.11	-0.66
R^2	0.12	0.12	0.10	0.12	0.10	0.13	0.10	0.10	-0.04	-0.03

Table B.12. Financial labor to total assets ratio and financial sector debt growth

This table reports the results of aggregate-level regressions of financial sector debt growth at $t+k$ on the labor to total assets ratio at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Because the financial sector labor to total assets ratio is non-stationary and falls during the sample, the predictor is 1-sided HP-filtered value of the ratio at t with a filtering parameter of 100. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with 1-side HP filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The online appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
ν_b	-0.84	-0.84	-0.49	-0.75	-0.78	-0.57	-0.92	-0.84	-0.74	-0.80
t	-3.09	-3.07	-2.10	-2.62	-3.57	-2.51	-3.16	-2.93	-3.01	-2.86
Control		0.02	1.39	0.85	-0.05	-0.02	0.05	0.00	0.00	0.00
t		0.02	4.74	3.92	-1.85	-1.27	0.98	-0.03	-1.75	-0.70
R^2	0.17	0.16	0.34	0.19	0.23	0.21	0.17	0.16	0.16	0.17
Panel B: 1-year ahead										
ν_b	-0.90	-0.92	-0.55	-0.73	-0.88	-1.05	-0.91	-0.83	-0.81	-0.66
t	-3.20	-3.16	-2.14	-2.52	-3.33	-3.35	-3.24	-2.68	-3.12	-3.85
Control		-1.20	1.38	1.61	-0.02	0.01	0.00	0.25	0.00	0.00
t		-1.63	3.46	3.63	-0.75	0.57	0.01	3.30	-1.81	-1.31
R^2	0.20	0.21	0.37	0.30	0.20	0.20	0.19	0.25	0.19	0.22
Panel C: 3-years ahead										
ν_b	-2.56	-2.57	-2.14	-2.38	-2.53	-2.73	-2.08	-2.41	-2.33	-1.34
t	-3.02	-3.02	-2.57	-2.75	-2.99	-3.39	-3.43	-2.67	-2.84	-1.95
Control		-1.15	1.64	1.67	-0.02	0.01	-0.28	0.51	0.00	-0.01
t		-0.39	1.36	2.51	-0.25	0.33	-1.35	2.63	-0.95	-1.80
R^2	0.22	0.20	0.23	0.22	0.20	0.20	0.24	0.23	0.15	0.28
Panel D: 5-years ahead										
ν_b	-4.32	-4.27	-4.02	-4.25	-4.30	-3.71	-3.22	-4.11	-3.00	-0.80
t	-2.70	-2.77	-2.50	-2.71	-2.66	-2.66	-2.73	-2.48	-1.98	-0.63
Control		5.11	1.16	0.62	-0.02	-0.04	-0.64	0.71	0.00	-0.01
t		1.16	0.58	0.32	-0.12	-0.95	-1.99	2.58	0.27	-1.69
R^2	0.23	0.23	0.22	0.21	0.21	0.23	0.30	0.24	0.09	0.20

Table B.13. Summary statistics, bank holding company

This table reports the summary statistics of bank holding companies and Compustat firms from our merged sample. The sample consists of annual observations from 1986 to 2019.

	Mean	SD	p25	p50	p75	Count
Size	19.96	1.38	18.95	20.27	21.30	17907
Capital ratio	0.08	0.02	0.07	0.08	0.10	17907
ROA	0.01	0.00	0.01	0.01	0.01	17907
NPL share	0.01	0.00	0.00	0.00	0.01	17907
Labor share	0.66	0.16	0.56	0.61	0.69	17907
Business Loan (Billion)	84.62	64.85	27.61	66.63	130.35	17907
Total Loan (Billion)	396.71	337.64	86.28	251.47	726.92	17907
Business Loan (to U.S firms) (Billion)	62.38	51.30	19.45	41.35	98.00	17907

Table B.14. Predicting U.S bank loan growth: other types of loans

This table reports the results of predicting loan growth in the U.S at $t+k$ by bank holding companies' labor share (FLS) at t using panel bank holding company data from FR Y-9C. This table presents both the univariate and multivariate regression results with bank holding company and state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$\Delta Loan_{i,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}$$

where $\Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t+1:t+k}) + Avg(Loan_{i,t-k+1:t})}$ is the loan growth of bank i over a 3-year window ($k = 3$). Column (1) to (4) present the predictability results with dependent variable to be growth rate of commercial and industrial (C&I) loan to U.S firms, column (5) to (8) present the predictability results with dependent variable to be growth rate of real estate loan and column (9) to (12) present the predictability results with dependent variable to be growth rate of consumer loan. The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The online appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using errors cluster over banks. The final sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	C& I (to U.S firms) loan growth				Real estate loan growth				Consumer loan growth			
FLS	-0.18***	-0.15***	-0.14***	-0.13***	-0.17***	-0.13***	-0.17***	-0.15***	-0.14***	-0.12***	-0.17***	-0.15***
	(-17.22)	(-14.68)	(-8.19)	(-7.53)	(-23.66)	(-19.51)	(-13.46)	(-13.07)	(-11.68)	(-9.73)	(-8.36)	(-6.91)
BHC Size			-0.08***	-0.07***			-0.08***	-0.09***			-0.10***	-0.09***
			(-5.87)	(-5.58)			(-8.33)	(-8.98)			(-6.22)	(-5.90)
BHC ROA			0.72	-0.15			0.21	-1.13			-2.28	-1.65
			(0.64)	(-0.13)			(0.25)	(-1.39)			(-1.62)	(-1.16)
BHC Capital ratio			0.34	0.57**			-0.28*	-0.14			-0.43	-0.14
			(1.49)	(2.47)			(-1.68)	(-0.89)			(-1.51)	(-0.48)
BHC NPL Share			-10.53***	-9.31***			-2.83***	-1.75***			-3.64***	-2.74***
			(-17.03)	(-14.92)			(-6.38)	(-3.92)			(-4.92)	(-3.63)
BHC Interest Expense			-2.93***	-2.18***			-5.30***	-4.45***			-3.77***	-2.73***
			(-4.32)	(-3.17)			(-9.11)	(-7.79)			(-4.11)	(-2.94)
BHC ΔEBIT			0.01***	0.01***			0.01***	0.01***			0.01***	0.00***
			(5.99)	(5.24)			(8.27)	(7.77)			(4.06)	(2.71)
N	36690	36567	32264	32128	36949	36837	32510	32385	36951	36839	32520	32395
adj. R^2	0.402	0.428	0.436	0.459	0.450	0.500	0.487	0.529	0.363	0.397	0.384	0.413
BHC FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table B.15. Bank level FLS and firm real outcomes, constrained subsample

This table reports the results of predictability of non-financial U.S firms' changes in investment rate, earnings growth and default risk over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. Firms are split into financially constrained and unconstrained, where constrained firms are defined to be in the top 33% of the sample by the Whited-Wu index. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$ for investment rate changes in Panel A and $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ for earnings growth in Panel B (k = 3). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio and interest expense) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return, tangibility and credit rating). The t-statistics reported in the parentheses below each coefficient estimate are obtained using errors cluster over bank and firm. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
	Constrained firms Top 33% of WW index			Unconstrained firms Bottom 33% of WW index		
	Panel A: Investment rate change					
FLS	-0.14	-0.33**	-0.17*	-0.01	-0.01	-0.02
	(-1.55)	(-2.34)	(-1.73)	(-0.42)	(-0.47)	(-0.64)
N	4672	4385	4656	5138	4772	5115
adj. R^2	0.284	0.283	0.299	0.198	0.224	0.233
	Panel B: Earnings growth					
FLS	-2.60*	-2.59*	-2.50*	-0.08	0.08	0.57
	(-1.75)	(-2.01)	(-1.76)	(-0.15)	(0.08)	(1.01)
N	4695	4404	4679	5186	4822	5164
adj. R^2	0.009	0.003	0.016	0.005	-0.011	0.007
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	Yes	No	No
State_Year FEs	No	Yes	No	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes	No	No	Yes

Table B.16. Correlations of extracted shocks

This table reports correlations for various ways to measure the financial sector's labor expense burden. FLS is the financial sector's labor share, as defined in section 2.2.1. As described in section 2.2.1, ϵ^1 is the shock to FLS, extracted by regressing it on several variables related to the business cycle, and ϵ^2 is the shock to FLS extracted through a VAR. ν_b is the financial sector's labor to asset share after a 1-sided HP-filtering to make it stationary, it is described in section 2.2.1; it is also the key shock in our model, as described in section 2.3.2. $\frac{N_b}{N}$ is the financial sector employment share of total employment, while we do not interpret it as a shock, as discussed in section 2.3.5, its behavior is closely related to the shocks in the model, and allows us to differentiate this model's predictions from several alternative models.

	FLS	ϵ_1	ϵ_2	ν_b	$\frac{N_b}{N}$
FLS	1.000	0.818	0.953	0.538	0.426
ϵ_1	0.818	1.000	0.834	0.288	0.319
ϵ_2	0.953	0.834	1.000	0.384	0.312
ν_b	0.538	0.288	0.384	1.000	0.676
$\frac{N_b}{N}$	0.426	0.319	0.312	0.676	1.000

Table B.17. Shock to bank labor expenses

In Panel A, we use the change in a bank's legal and processing fees scaled by total assets (defined for each bank i and year t) to instrument for FLS. Column (1) reports results from the first stage of regressing the change in a bank's FLS on the contemporaneous change in its legal and data processing fees, the unit of observation is bank-year. We define $\Delta\widehat{FLS}_{t,i}$=0.062 + 79.9*(Δ Legal and data processing fees / TA)$_{t,i}$. Column (2) reports results from regressing the a bank's three-year loan growth from [t-2:t] to [t+1:t+3] on $\Delta\widehat{FLS}$. Column (3) reports results from regressing the average loan spreads (measured as "All-indrawn" from Dealscan Loan Pricing) for the loans that the bank issues from t+1 to t+3 on $\Delta\widehat{FLS}$. The unit of observation is bank-year and we aggregate the loan-level measures to the bank-year level for all loans available in Dealscan issued by a particular bank, weighted by the individual loan amount. Therefore, the number of observation in column (3) is substantially smaller as the number of banks in Dealscan is very small. Panel B is similar but we instrument for FLS with the regulatory burdens measure where $\Delta\widehat{FLS}_{t,i}$=0.045 + 0.259*(Δ Regulatory Burden)$_t$. Column (4) of Panel B shows that the change in the legal and data processing fees (the instrument in Panel A) is also related to regulatory burden.

	(1) FLS	(2) Loans	(3) Spread	(4) Legal and data processing fees x 1000 / Total Assets
Panel A: Legal and Processing fees as IV				
Legal and data processing fees / TA	79.907***			
	(6.57)			
$\widehat{FLS}$		-0.251***	1.622**	
		(-6.95)	(2.16)	
Bank controls	-	Yes	Yes	
Firm and Loan controls	-	-	Yes	
N	15487	13021	316	
adj. R^2	0.007	0.581	0.611	
FEs	-	Bank and year	Bank	
Panel B: Regulatory Burden as IV				
Regulatory Burden	0.259***			0.193***
	(4.14)			(3.83)
$\widehat{FLS}$		-0.985***	1.690**	
		(-14.42)	(2.15)	
Bank controls	-	Yes	Yes	Yes
Firm and Loan controls	-	-	Yes	-
N	17426	14920	351	15218
adj. R^2	0.002	0.472	0.575	-0.033
FEs	-	Bank	Bank	Bank

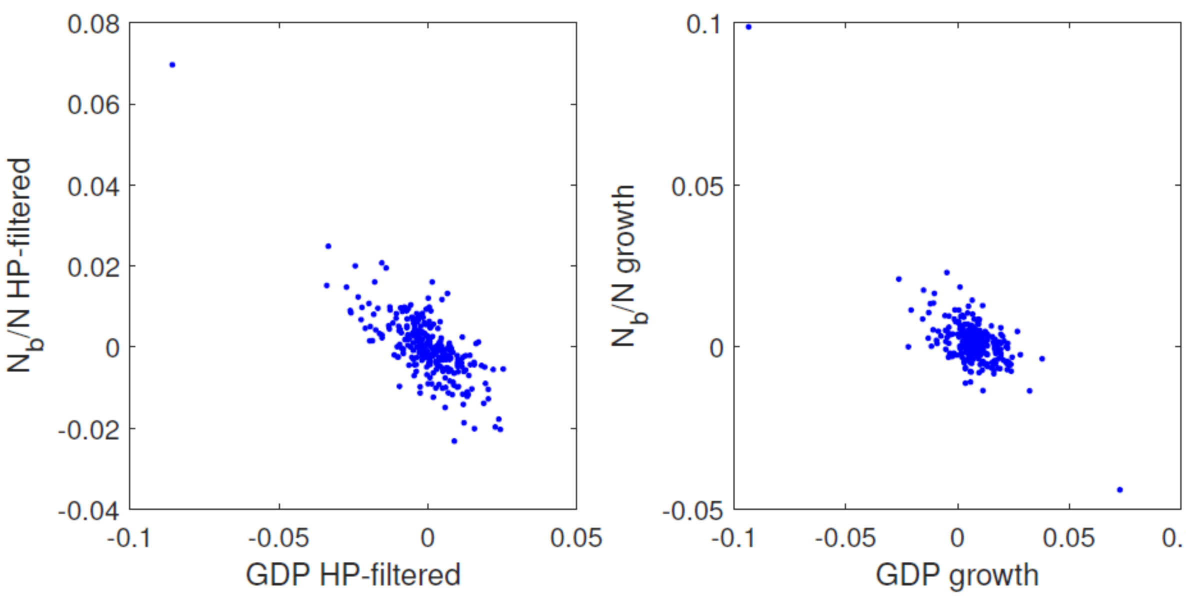
Table B.18. Cyclicality of labor relative to aggregate labor for selected industries

This table computes the cyclicality of an industry's employment share of total employment for selected industries likely to have high human capital. The first column presents the correlation of HP-filtered N_i/N with HP-filtered real GDP, while the second column presents the correlation of growth rates. All variables are from FRED. Real GDP is defined as GDPC1, financial employment is USFIRE, while the other variables can be found in Table B-1, Employees on nonfarm payrolls by industry sector.

	HP filter	Growth
	Broad categories, 1952-2019	
Finance	-0.668	-0.469
Information	0.171	0.132
Professional Services	-0.156	-0.096
Education and Health	-0.690	-0.542
	Finer categories, 1990-2019	
Finance	-0.297	-0.081
Computer and electronic manufacturing	0.054	0.054
Computing Infrastruct., Data Processing, Web Hosting	-0.034	0.085
Telecommunication	-0.108	0.142
Professional, Scientific, And Technical Services	0.010	0.106
Legal Services	-0.448	-0.285
Accounting services	-0.069	0.072
Architectural and Engineering	0.205	0.254
Computer system design	0.162	0.230
Management and technical consulting	-0.110	0.067
Healthcare and Social Assistance	-0.652	-0.560
Non-Fin, Non-Healthcare average	-0.038	0.081

Figure B.2. Financial sector employment share of total employment, scatter plot

This figure plots a scatter plot of the financial sector employment share of total employment compared to GDP. The series are USFIRE, PAYEMS, and GDPC1 respectively in FRED. Since both series are non-stationary, the left panel plots HP-filtered values and the right growth rates.



B.3 Model extensions

This section shows that the frictionless version of our model with 2-period firms is isomorphic to the standard problem with dynamic firms. It then presents two model extensions: a model with credit risk and a model with wage rigidity in the FI sector.

B.3.1 Solution of frictionless model

Plugging equation 2.6 for Q_t into equation 2.4 for $V_{t+1,co}$, noting that $S_{t+1} = K_{t+2}$ and rearranging, we can rewrite the old firm's value at $t+1$ as:

$$V_{t+1,co} = \left(X_{t+1} + 1 - \delta + \nu_{k,0}(2\nu_{k,1} - 1)\left(\frac{K_{t+2}}{K_{t+1}} - \nu_{k,1}\right) + 2\nu_{k,0}\left(\frac{K_{t+2}}{K_{t+1}} - \nu_{k,1}\right)^2 \right) K_{t+1}. \tag{B.3}$$

This implies that the equity return is

$$R_{t+1} = \frac{V_{t+1,co}}{V_{t,cn}} = \frac{X_{t+1} + 1 - \delta + \nu_{k,0}(2\nu_{k,1} - 1)\left(\frac{K_{t+2}}{K_{t+1}} - \nu_{k,1}\right) + 2\nu_{k,0}\left(\frac{K_{t+2}}{K_{t+1}} - \nu_{k,1}\right)^2}{1 + 2\nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)}, \tag{B.4}$$

where the numerator comes from $V_{t,cn} = Q_t K_{t+1}$. From footnote 39 in the main text:

$$X_t = \alpha Z_t \left(\frac{K_t}{N_t}\right)^{\alpha - 1}. \tag{B.5}$$

The household's problem leads to the standard Euler equation:

$$1 = E_t\left[\beta \left(\frac{C_{t+1}}{C_t}\right)^{-\rho} R_{t+1}\right]. \tag{B.6}$$

The aggregate budget constraint is:

$$C_t = Z_t K_t^{\alpha} N_t^{1-\alpha} + (1-\delta)K_t - K_{t+1} - \nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t. \tag{B.7}$$

Equations B.4, B.5, B.6, and B.6 can be combined into a single functional equation with a single unknown: K_{t+1} as a function of the state (Z_t, K_t).

We now show that the more standard specification of a dynamic firm with adjustment costs leads to exactly the same equation, therefore, the two problems are isomorphic. Consider an infinitely lived firm maximizing the present value of future dividends:

$$V_t = Z_t K_t^{\alpha} N_t^{1-\alpha} - W_t N_t + K_t(1-\delta) - K_{t+1} - \nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t + E_t[M_{t+1} V_{t+1}]. \tag{B.8}$$

Exactly as in the main text, this can be rewritten as

$$V_t = X_t K_t + K_t(1-\delta) - K_{t+1} - \nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t + E_t[M_{t+1} V_{t+1}]. \tag{B.9}$$

One can guess and verify that the value function is linear in capital: $V_t = Q_t K_t$. In doing so, the firm's first order conditions imply that

$$\frac{K_{t+1}}{K_t} = \nu_{k,1} + \frac{E_t\left[M_{t+1}Q_{t+1} - 1\right]}{2\nu_{k,0}}. \tag{B.10}$$

Plugging equation B.10 into equation B.9 to substitute out $E_t[M_{t+1}V_{t+1}]$ and rearranging leads to exactly the same equation as equation B.3, that is $V_{t+1} = V_{t+1,co}$.

The firm's equity return is $R_{t+1} = \frac{V_{t+1}}{V_t - Div_t}$ where $V_t - Div_t = E_t[M_{t+1}Q_{t+1}] = \left(1 + 2\nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)\right)K_t$ and equation B.10 is used to derive the last equality. Plugging the equations for V_{t+1} and $V_t - Div_t$ into R_{t+1} leads to an equation identical to equation B.4. Equations B.5, B.6, and B.7 are also identical in both problems as they are unaffected by whether the firm is dynamic or not. Therefore, the solutions to both problems are characterized by exactly the same four equations.

B.3.2 Model with credit risk

In this subsection, we extend the baseline model to allow for risky corporate debt. The household's problem remains identical to the baseline model.

For firms, we add a shock which determines default. A fraction p^{δ}_{t+1} of firms suffer a big depreciation shock – a fraction $\overline{\delta}_{t+1}$ of the capital depreciates after production, where $\overline{\delta}_{t+1}$ is a large number close to one. These firms do not produce new capital. We calibrate the shocks so that p^{δ}_{t+1} is the default rate because firms who lose most of their capital are unable to pay back their debts; we choose $\overline{\delta}_{t+1}$ to roughly match the recovery rate. Firms that do not suffer a big depreciation shock see their capital depreciate at a normal rate $\underline{\delta}_{t+1}$, implying that the aggregate capital depreciation rate is $\delta = 1 - (1 - p^{\delta}_{t+1})(1 - \underline{\delta}_{t+1}) - p^{\delta}_{t+1}\overline{\delta}_{t+1}$. We choose $\underline{\delta}_{t+1}$ such that the aggregate depreciation rate δ is always constant, however, the default rate p^{δ}_{t+1} and recovery rate (closely related to $1 - \overline{\delta}_{t+1}$) may be time varying. When p^{δ}_{t+1} and $\overline{\delta}_{t+1}$ are constant, then there is no aggregate variation in the default rate and the default shock is purely cross-sectional.

All firms take wages as given and make identical labor decisions, leading to exactly the same equations for N_t and X_t as in the case with safe corporate debt.

Those firms whose capital did not depreciate choose how much new capital S_{t+1} to create, pay adjustment costs associated with creation of new capital,[3] sell their capital to newly formed firms for $S_{t+1}Q_{t+1}$, sell their output, pay labor costs, pay the proceeds to their equity owners, and shut down. Those firms whose capital fully depreciated simply sell their output, pay labor costs, sell their undepreciated capital, pay the proceeds to creditors, and shut down. The equity and debt values as a function of possible shock realizations

[3] We choose the adjustment cost function $\nu_{k,0}\left(\frac{S_t(1-p^{\delta}_t)}{K_t} - \nu_{k,1}\right)^2 K_t$, which differs from the original function because of $1 - p^{\delta}_t$ in the numerator. Since only those firms whose capital does not fully depreciate are able to produce new capital, the relationship between the capital created by an individual firm S_t and aggregate per capita capital K_{t+1} is $K_{t+1} = S_t(1 - p^{\delta}_t)$. This implies that the aggregate adjustment cost is $\nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t(1 - p^{\delta}_t)$ and the aggregate cost of capital is $Q_t = 1 + 2\nu_{k,0}(\frac{K_{t+1}}{K_t} - \nu_{k,1})(1 - p^{\delta}_t)$. We chose this functional form because it implies that the level of capital growth K_{t+1}/K_t associated with zero adjustment costs is equal to a constant $\nu_{k,1}$, just as in the version without default. The alternative would be to allow the level of capital growth K_{t+1}/K_t associated with zero adjustment costs to be time varying, which is analogous to having a time varying $\nu_{k,1,t}$. Investment and stock returns in the alternative specification behave quite differently from the standard model and we find this unappealing. However, the bank labor channel we study in this paper is not affected by the choice of the adjustment cost specification.

is written below:

Shock	Fraction	Equity $V_{t+1,co}$	Debt
Depr.	p^{δ}_{t+1}	0	$\left(\left(1-\nu_{cd,0}\zeta_t^2\right)X_{t+1}+1-\overline{\delta}_{t+1}\right)K_{t+1}$
No Depr.	$1-p^{\delta}_{t+1}$	$\left(\left(1-\nu_{cd,0}\zeta_t^2\right)X_{t+1}K_{t+1}+1-\underline{\delta}_{t+1}\right)K_{t+1}-B_{t+1,cd}$ $-S_{t+1}-\nu_{k,0}\left(\frac{S_{t+1}(1-p^{\delta}_{t+1})}{K_{t+1}}-\nu_{k,1}\right)^2 K_{t+1}+Q_{t+1}S_{t+1}.$	$B_{t+1,cd}$

(B.11)

The average values of the equity payout across all firms is:

$$V_{t+1,co} = (1-p^{\delta}_{t+1}) \Big(\left(\left(\left(1-\nu_{cd,0}\zeta_t^2\right)X_{t+1}+1-\underline{\delta}_{t+1}\right)K_{t+1}-B_{t+1,cd} -S_{t+1}-\nu_{k,0}\left(\frac{S_{t+1}(1-p^{\delta}_{t+1})}{K_{t+1}}-\nu_{k,1}\right)^2 K_{t+1}+Q_{t+1}S_{t+1}\Big), \tag{B.12}$$

while for debt it is:

$$\text{Debt Payout} = (1-p^{\delta}_{t+1})B_{t+1,cd}+p^{\delta}_{t+1}\left(\left(1-\nu_{cd,0}\zeta_t^2\right)X_{t+1}+1-\overline{\delta}_{t+1}\right)K_{t+1}. \tag{B.13}$$

The investment decision is orthogonal to the production decision, therefore all firms with undepreciated capital will make identical investment decisions and their FOC for investment implies:

$$Q_{t+1} = 1+2\nu_{k,0}(1-p^{\delta}_{t+1})\left(\frac{S_{t+1}(1-p^{\delta}_{t+1})}{K_{t+1}}-\nu_{k,1}\right) = 1+2\nu_{k,0}(1-p^{\delta}_{t+1})\left(\frac{K_{t+2}}{K_{t+1}}-\nu_{k,1}\right), \tag{B.14}$$

where the last equality is true because in aggregate, $1-p^{\delta}_{t+1}$ of the firms produce new capital $S_{t+1,i}$:

$$K_{t+1} = S_t(1-p^{\delta}). \tag{B.15}$$

The firm's capital structure decision is independent of the investment decision – the firm chooses debt to maximize expected cashflows to equity holders $-V_{t,cn}+E_t[M_{t+1}V_{t+1,co}]$ (note that this quantity is zero in equilibrium since equity is fairly priced). The choice of debt therefore satisfies:

$$1-E_t[\widehat{M}^c_{t+1}(1-p^{\delta}_{t+1})]R_{t,cd} = 2\nu_{cd,0}\left(\frac{B_{t+1,cd}/R_{t,cd}}{K_{t+1}}-\nu_{cd,1}\right)E_t[\widehat{M}^c_{t+1}(1-p^{\delta}_{t+1})X_{t+1}]. \tag{B.16}$$

The bank's problem is similar to before but its payout is now risky and depends on the default rate.

$$\begin{aligned}
V_{t+1,bo} &= B_{t+1,cd}-B_{t+1,d} \\
&= V_{t,bn}\left((1+\kappa)(1-\nu_{b,t}W_t)\tilde{R}_{t+1,cd}-\kappa R_{t,d}\right) \\
B_{t+1,d}/R_{t,d} &= \kappa V_{t,bn} \\
N_{t,b} &= \nu_{b,t}\left(V_{t,bn}+B_{t+1,d}/R_{t,d}\right) \\
&= V_{t,bn}\nu_{b,t}(1+\kappa) \\
B_{t+1,cd}/R_{t,cd} &= V_{t,bn}+B_{t+1,d}/R_{t,d}-W_tN_{t,b} \\
&= V_{t,bn}(1+\kappa)(1-\nu_{b,t}W_t) \\
\tilde{R}_{t+1,cd} &= (1-p^{\delta}_{t+1})R_{t,cd}+p^{\delta}_{t+1}\frac{\left(\left(1-\nu_{cd,0}\zeta_t^2\right)X_{t+1}+1-\underline{\delta}_{t+1}\right)K_{t+1}}{B_{t+1,cd}},
\end{aligned} \tag{B.17}$$

where the bank's risky realized return on corporate debt lending is $\tilde{R}_{t+1,cd}$.

The equilibrium and solution methods are analogous to the problem with safe debt. Many of the parameters are identical to the baseline model without credit risk, here we discuss those that are different. The time discount factor $\beta = 0.991$ is higher to match the capital to output ratio. The capital adjustment cost is $\nu_{k,0} = 1.0$ to match investment volatility. The grid for the financial sector labor to assets ratio is $\nu_{b,t} = (0.0178, 0.0140, 0.0102)$ to match the average labor share and the volatility of financial employment as a share of total employment.

Additionally, the model with default requires the calibration of the probability of default p_t^δ and depreciation shock $\overline{\delta}_t$. These random variables take on three possible values, just like TFP Z_t and are perfectly negatively correlated with Z_t, with probability of default and depreciation shock highest (recovery lowest) when TFP is low. However, note that these two variables are designed to have only cross-sectional effects, neither one directly affects aggregate output or investment. We choose these values based on estimates in (Bruche and Gonzalez-Aguado, 2010), where default rates are between 0.01 in good times and 0.04 in bad times, and recovery rates are between 0.50 in good times and 0.20 in bad times.[4]

Figures B.3 and B.4 show the impulse responses of various quantities after a shock to FLN, or to aggregate TFP, respectively. They are analogous to figures 2.1 and 2.2 in the main text. The response to an FLN shock is similar – qualitatively and quantitatively – to the baseline model. Therefore, credit risk, while realstic, is not important for understanding our channel of interest.

Recall that in the baseline model, the impulse responses of labor share, corporate spreads, and corporate lending to a TFP shock were quite different than to an FLN shock. Unlike the baseline model, in the model with credit risk, the impulse responses to a TFP shock are qualitatively similar to the impulse responses to an FLN shock. In the baseline model, financial sector labor share falls after a negative TFP shock because the interest rate on corporate lending rises, leading to an increase in the financial sector's value added, which is counterfactual. In the model with credit risk, upon impact of a negative TFP shock, some firms default, causing value added to fall and labor share to rise. Labor share then falls the following period as credit spreads adjust. Output and investment fall as they are impacted by the TFP shock directly. The corporate spread rises due to higher default risk, and corporate lending falls. Equity prices fall at the time the negative TFP shock is realized, but the equity premium rises going forward for the same reason as in the baseline model – firms shift from debt toward equity financing.

Despite the qualitative similarities to the FLN shock, the quantitative effect on credit markets is much weaker. The changes to debt issuance and corporate spreads are just one third that of the FLN shock. Furthermore, although financial sector labor share rises initially due to unexpected defaults, it immediately falls below its pre-shock level the next period as credit spreads rise. This is different from an FLN shock, after which the financial sector labor share remains persistently elevated.

B.3.3 Model with wage rigidity

In this subsection, we extend the baseline model to allow for wage rigidity in the financial sector. Most parts of the model remain identical to the previous section, however, we now differentiate between the wage in the financial sector $W_{t,f}$ and the wage in the productive sector $W_{t,p}$.

The productive sector wage is chosen to clear labor market, just as before. However, the financial sector wage follows the equation $W_{t,f} = \mu W_{t-1,f} + (1-\mu) W_{t,p}$ if $W_{t-1,f} > W_{t,p}$ and $W_{t,f} = W_{t,f}$ otherwise. This implies that financial sector wages are always at least as high as economy wide wages, and that there is downward rigidity in the financial sector. Since financial sector wages are higher, all employees would prefer to work in the financial sector. Without rigidity, this would push financial sector wages down. However,

[4] In the model, the capital to output ratio is 2.6, implying profit to capital of around $\alpha/2.6 = 0.13$. If between 0 and 0.12 of capital is recovered, then total amount recovered by creditors is between 0.13 and 0.25 of capital. The corporate debt to capital ratio is around 0.36, implying recovery rates between 0.35 and 0.70.

since the financial sector cannot lower its wages, it chooses employment $N_{t,b}$ given its (higher) wages by hosting a lottery; the remaining workers work in the productive sector and $W_{t,p}$ clears supply and demand in the corporate labor market. The aggregate wage is $N_{t,b}W_{t,b} + N_{t,c}W_{t,p}$ and all workers pool resources, thus only the aggregate wage matters for the representative agent.

To focus on the effect of rigidity, we shut down FLN shocks ($\nu_{b,t}$), thus TFP shocks are the only shocks driving the model. We also focus on the model with credit risk because, as discussed above, without credit risk, a negative TFP shock causes a fall in financial sector labor share. The parameters of this model are identical to the credit risk model, with the exception of $\nu_{b,t}$, which is contant and equal to its mean value in the credit risk model.

In Appendix figure B.5 we compare a model with rigidity ($\mu = 0.9$) to one without ($\mu = 0$). $\mu = 0.9$ implies that wages are unchanged, on average, 10 years. This is likely much stronger than rigidity in the real world, despite this, the effect of rigidity is quantitatively small. Financial sector labor share is higher after a negative TFP shock, but the effect is too small to see in the figure. Similarly, output and investment are lower in the wage rigidity model after a negative TFP shock, however, the effects are too small to be seen in figure. The corporate spread rises by 10% in the model with rigidity, comapred to 9% without rigidity. The biggest effect is on corporate lending, which falls by 3% in the model with wage rigidity, compared to 2% in the model without. All effect are much smaller than from an FLN shock.

B.3.4 Constructing the transition probability matrix

Recall that our goal is to construct a discrete Markov process with 9 states such that Z_t and $\nu_{b,t}$ are functions of the 9 states, the HP-filtered autocorrelation of output (endogenous quantity closely related to Z_t) is 0.33, the HP-filtered autocorrelation of $\nu_{b,t}$ is 0.50, and the correlation of the two HP-filtered quantities is -0.23.

We start with a symmetric 3-state Markov process for Z_t with transition probabilities $p_z = (0.6, 0.3, 0.1; 0.2, 0.6, 0.2; 0.1, 0.3, 0.6)$. Similarly, we start with a symmetric 3-state Markov process for $\nu_{b,t}$ with transition probabilities $p_\nu = (0.8, 0.2, 0.0; 0.1, 0.8, 0.1; 0.0, 0.2, 0.8)$. For each Markov process, a low realization was assigned a value of 1, a medium a value of 2, and a high a value of 3. To combine these into a 9-state Markov process in which Z_t and $\nu_{b,t}$ are independent, one would take a Kronecker product, however we target a negative correlation between Z_t and $\nu_{b,t}$, therefore follow a more complicated procedure below.

Next, we simulated two independent AR(1) processes: $x^Z_{t+1} = (1-\rho^Z)\mu^Z + \rho^Z x^Z_t + \sigma^Z \epsilon^Z_{t+1}$ and $x^\nu_{t+1} = (1-\rho^\nu)\mu^\nu + \rho^\nu x^\nu_t + \sigma^\nu \epsilon^\nu_{t+1}$ with uncorrelated $\epsilon^Z \approx N(0,1)$ and $\epsilon^\nu \approx N(0,1)$. We chose the parameters such that these two processes have the same autocorrelations and the same number of low (1), medium (2), and high (3) realizations as the analogous p_z and p_ν discrete processes above. Since x^Z and x^ν are continuous, in order to count the number of low, medium, and high realizations, we discretize them by rounding their values to the nearest integer, by setting any value below 1 to 1, and any value above 3 to 3. Define the discretized value of x to be $\hat{x}$. The parameter values $\mu^Z = 2$, $\rho^Z = 0.6$, $\sigma^Z = 0.69$, $\mu^\nu = 2$, $\rho^\nu = 0.92$, and $\sigma^\nu = 0.3$ achieve the goal stated above.

We then change the correlation between ϵ^Z and ϵ^ν to $\rho^{Z,\nu} = 0.5$ and resimulate the above process. Note that Z_t and $\nu_{b,t}$ need to be negatively correlated. We set the correlation between x^Z and x^ν (similarly between $\hat{x}^Z$ and $\hat{x}^\nu$) to be positive, but we set the grid for $\nu_{b,t}$ such that $\nu_{b,t}$ is high when $\hat{x}^\nu$ is low, leading to a negative correlation between Z_t and $\nu_{b,t}$.

Finally, we create a 9-state transition probability matrix by counting the total number of transitions from each possible state to each other possible state. Specifically, since $\hat{x}^Z \in (1,2,3)$ and $\hat{x}^\nu \in (1,2,3)$, we combine them into a 9-state process by defining the state as $i = (\hat{x}^Z_t - 1) * 3 + \hat{x}^\nu_t \in (1, \ldots 9)$. We then define the transition probability matrix as $p_{i,j} = \frac{\sum (\hat{x}^Z_t - 1)*3 + \hat{x}^\nu_t = i \quad \& \quad (\hat{x}^Z_{t+1} - 1)*3 + \hat{x}^\nu_{t+1} = j}{\sum (\hat{x}^Z_t - 1)*3 + \hat{x}^\nu = i}$. We set any entries below 0.002

to 0 and redistribute these values to other entries. The resultant transition probability matrix used in the paper is:

$$p = \begin{pmatrix} 0.5380 & 0.0613 & 0.0000 & 0.2309 & 0.1128 & 0.0000 & 0.0235 & 0.0337 & 0.0000 \\ 0.0847 & 0.4547 & 0.0050 & 0.0103 & 0.3597 & 0.0202 & 0.0000 & 0.0544 & 0.0110 \\ 0.0000 & 0.2203 & 0.2612 & 0.0000 & 0.0606 & 0.3784 & 0.0000 & 0.0000 & 0.0795 \\ 0.2468 & 0.0118 & 0.0000 & 0.3859 & 0.1379 & 0.0000 & 0.0910 & 0.1266 & 0.0000 \\ 0.0415 & 0.2027 & 0.0000 & 0.0196 & 0.4714 & 0.0216 & 0.0000 & 0.2032 & 0.0401 \\ 0.0000 & 0.1235 & 0.0935 & 0.0000 & 0.1264 & 0.3892 & 0.0000 & 0.0143 & 0.2532 \\ 0.0748 & 0.0000 & 0.0000 & 0.3449 & 0.0717 & 0.0000 & 0.2843 & 0.2244 & 0.0000 \\ 0.0104 & 0.0541 & 0.0000 & 0.0188 & 0.3583 & 0.0101 & 0.0052 & 0.4562 & 0.0869 \\ 0.0000 & 0.0334 & 0.0198 & 0.0000 & 0.1127 & 0.2359 & 0.0000 & 0.0583 & 0.5399 \end{pmatrix}$$

We then convert the 9 Markov states into values for Z_t and $\nu_{b,t}$ using the mapping

$$Z \in (0.95, 0.95, 0.95, 1.00, 1.00, 1.00, 1.05, 1, 05, 1.05)$$
$$\nu_b \in (0.0223, 0.0180, 0.0137, 0.0223, 0.0180, 0.0137, 0.0223, 0.0180, 0.0137),$$

where these values are chosen to match the volatilities of output and financial sector labor, as explained in sectin 2.3.3. The simulated model moments implied by the transition probability matrix are 0.24 for the autocorrelation of HP-filtered GDP, 0.42 for the autocorrelation of HP-filtered financial labor to financial capital (ν_b), and -0.36 for the correlation of the two, compared to targets of (0.33,0.50,-0.23).

Note that the inputs into the above algorithm were the two univariate transition probability matricies p_z and p_ν, and the correlation $\rho^{Z,\nu}$. These were not chosen arbitrarily but rather were the result of an iterative procedure where we updated their values to get model moments closer to targets. Above, we only report the final p_z, p_ν, and $\rho^{Z,\nu}$.

B.3.5 Solution algorithm

The model described in Section 3.2 is non-stationary. Before solving it numerically, it must be detrended by its balanced growth path $(1+g)^t$. The non-stationary variables Z_t, K_t, W_t, C_t, NW_t, $V_{t,cn}$, $V_{t,bn}$, $V_{t,co}$, $V_{t,bo}$, B_t, and S_t are all detrended by $(1+g)^t$; the value function $U(NW_t)$ is detrended by $(1+g)^{t(1-\rho)}$; the variables $N_{t,c}$, Q_t, $R_{t,i}$, $\theta_{t,i}$, M_t, $\nu_{b,t}$, ζ_t, and Ψ_t do not need to be detrended as they are stationary. After detrending, we can rewrite all of the equations in Section 3.2 as analogous equations but in terms of stationary variables. We use lower case letters to refer to the detrended stationary variables.

We then solve the model numerically. Note that because firms and banks in our model live for only two periods, we can solve their problems analytically as a function of the aggregate state. Furthermore, because of the overlapping generation set up, we do not need to keep track of and approximate the cross-sectional distribution of capital and productivity across firms. Therefore, our state space is the true state space, rather than an approximation of the true state space, as is often the case in models with heterogenous firms or agents. The state space includes four variables: the TFP shock z_t, the labor need shock $\nu_{b,t}$, the aggregate capital stock k_t, and the deviation from optimal capital structure ζ_{t-1}. The first two are exogenously specified Markov shocks whose realizations and transition probabilities are described in Section B.3.4. On the other hand k_t and ζ_{t-1} are endogenous; we discretize them on grids of sizes 40 and 11, respectively. We define $\Gamma_t = (z_t, \nu_{b,t}, k_t, \zeta_{t-1})$ as the aggregate state.

We begin by specifying a set of beliefs for k_{t+1}, ξ_t, c_t, w_t, and $v_{t,bn}$ as functions of the aggregate state Γ_t.[5] Note that since $\Gamma_{t+1} = (z_{t+1}, \nu_{b,t+1}, k_{t+1}, \xi_t)$, and since z_{t+1} and $\nu_{b,t+1}$ are exogenous random shocks with known probability distributions, the specified beliefs also provide us with a belief about the evolution of the aggregate state Γ_{t+1}. We use the term beliefs because in partial equilibrium, we can solve the firm's, bank's, and household's problems for any set of beliefs. However, since we are solving for a rational expectations equilibrium, in equilibrium the beliefs will be consistent with the actual behavior of these variables.

Using the specified beliefs, we are able to analytically solve the firm's problem (including the distribution of its equity return $R_{t+1,c}$), the bank's problem (including the distribution of its equity return $R_{t+1,b}$), the deposit rate $R_{t,d}$, the corporate borrowing rate $R_{t,cd}$, and the quantity of corporate debt $B_{t+1,cd}$. This is discussed in detail in Section B.3.5 below. The returns $R_{t+1,c}$, $R_{t+1,b}$, $R_{t+1,d}$, and $R_{t+1,cd}$ are functions of the state Γ_t, and in the case of $R_{t+1,c}$ and $R_{t+1,b}$ also of the realized shocks z_{t+1} and $\nu_{b,t+1}$. These are also beliefs, since we solve them conditional on the initially specified beliefs.

With beliefs about rates of return ($R_{t+1,c}$, $R_{t+1,b}$, and $R_{t+1,d}$), wages (w_t), and the evolution of the aggregate state (Γ_{t+1}), all as functions of the state and of the realized shock, it is straight forward to solve the household's problem in partial equilibrium. We are solving for a decentralized equilibrium, therefore, even though there is a representative agent, the household thinks of itself as atomistic when solving its problem. The household's individual state includes its individual wealth nw_t[6] and the aggregate state Γ_t. We discretize nw_t using a grid of size 40 and solve the household's problem using backward value function iteration. This gives us the household's policies for consumption c_t and portfolio choice $\theta_{t+1,c}$ and $\theta_{t+1,b}$ as functions of nw_t and Γ_t.

Next, starting at every possible point on the aggregate state space Γ_t, we use the policy functions to simulate the model one period forward. We do this in order to solve for the actual k_{t+1}, ξ_t, c_t, w_t, $V_{t,bn}$, and $N_{b,t}$ as functions of the aggregate state Γ_t. We then use these values to update the beliefs, putting a weight of 0.975 on old beliefs in each iteration in order to ensure a smooth convergence. Once the beliefs have been updated, we restart the process and repeat until convergence. There is one complication associated with clearing markets while simulating the model, which we describe below in Section B.3.5.

Clearing markets during simulation

The household's policies are functions of both the aggregate state Γ_t and of individual wealth nw_t, therefore, we cannot simulate the problem for each point of the aggregate state if we do not know individual wealth nw_t. In equilibrium, $nw_t = v_{t,co} + v_{t,bo} + b_{t+1,d}$ (equation 2.7), however, we cannot solve for $v_{t,co}$ without knowing aggregate investment s_t (equations 2.6 and 2.10), and we cannot solve for aggregate investment s_t without knowing aggregate consumption c_t (equation 2.17), which is itself a function of nw_t. Thus, the problem is circular. For this reason, when simulating this problem, at each point in the state space (or equivalently, each period if we are interested in a long simulation), we solve a fixed point problem to clear markets. We start with a guess for c_t, use equation 2.17 to solve for s_t, use equations 2.6 and 2.10 to solve for $nw_t = v_{t,co} + v_{t,bo}$[7], which we then use to update the policy c_t. We repeat this until convergence, that is, until we found a c_t such that markets clear.

[5] Even though k_{t+1} and ξ_t are part of the $t+1$ state Γ_{t+1}, they are both determined at t and are functions of Γ_t.

[6] In equilibrium, household wealth is related to the aggregate state through equation 2.7.

[7] In equilibrium, the bank's value plus the value of deposits $v_{t,bo} + b_{t+1,d}$ is equal to the bank's revenue, which is the firm's payout of corporate debt $b_{t+1,cd}$. Therefore, to solve for $nw_t = v_{t,co} + v_{t,bo} + b_{t+1,d}$, we can simply solve for the unlevered value of the firm using equation 2.10. In this equation, we set $b_{t+1,cd} = 0$ since ultimately, any debt paid out by the firm still belongs to the representative agent, however, we keep ζ_{t-1} unchanged, reflecting losses in output due to deviations from optimal capital structure.

Analytic solutions of firm and bank problems

Here we describe how to analytically solve the firm's and bank's problems starting from beliefs about k_{t+1}, ξ_t, c_t, w_t, and $v_{t,bn}$.

Using beliefs about c_t as a function of the state Γ_t and using beliefs about the transition of the state Γ_{t+1}, we can construct next period's c_{t+1} as a function of the state and the realized shocks. This can be used to construct the stochastic discount factor M_{t+1} and to solve for $b_{t+1,d}/R_{t,d}$ (equation 2.8).

Starting with beliefs about $v_{t,bn}$, one can solve for $b_{t+1,d}/R_{t,d}$ (equation 2.13), $N_{t,b}$ (equation 2.14), $b_{t+1,cd}/R_{t,cd}$ (equation 2.15 combined with belief about w_t). Combining the household's and bank's equations for $b_{t+1,d}/R_{t,d}$, we can solve for $b_{t+1,d}$ and $R_{t,d}$ independently.

Given beliefs about k_{t+1}, we can solve for $s_{t+1} = k_{t+1}$ and q_t (equation 2.6). Then using k_{t+1}, q_t, and $b_{t+1,cd}/R_{t,cd}$ from the bank's problem, we can solve for $v_{t,cn}$ (equation 2.9). Using k_{t+1}, q_t, $v_{t,cn}$, M_{t+1}, and $\theta_{t+1,c} = 1$ (equilibrium), we can solve for $\widehat{M}^c_{t+1}$ (equation 2.8). Given beliefs about w_t, we can solve for x_t (equation 2.11). We can combine $\widehat{M}^c_{t+1}$ and x_t to solve for the two expectations in equation B.16. We can then combine equation B.16 with $b_{t+1,cd}/R_{t,cd}$ from the bank's problem to solve for $b_{t+1,cd}$ and $R_{t,cd}$ independently.

Similar to our earlier construction of c_{t+1}, using beliefs about k_{t+1}, w_t, and $v_{t,bn}$ as functions of the state Γ_t and using beliefs about the transition of the state Γ_{t+1}, we can construct next period's k_{t+2}, w_{t+1}, and $v_{t+1,bn}$. We can use k_{t+2} to construct q_{t+1} (equation 2.6) and use $v_{t+1,bn}$ to construct $N_{t+1,b}$. We now have all the inputs to solve for the firm's realized equity value $v_{t+1,co}$ (equation 2.10). We also have everything we need to consruct $v_{t+1,bo}$ (equation 2.16). These can be combined with the $v_{t,cn}$ (solved earlier) and $v_{t,bn}$ (belief) to solve for the equity returns of the firm and the bank.

Figure B.3. Impulse responses to an FLN shock in a model with credit risk

This figure plots the impulse response functions to a one standard deviation shock to the FLN, $\nu_{b,t}$. To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the FLN shock at their average values. At $t = 1$, the TFP shock remains at its average value, but the FLN shock rises unexpectedly. After $t = 1$, the TFP shock remains at its average value, while the FLN shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a high $\nu_{b,t}$, while $t > 1$ values are expected values.

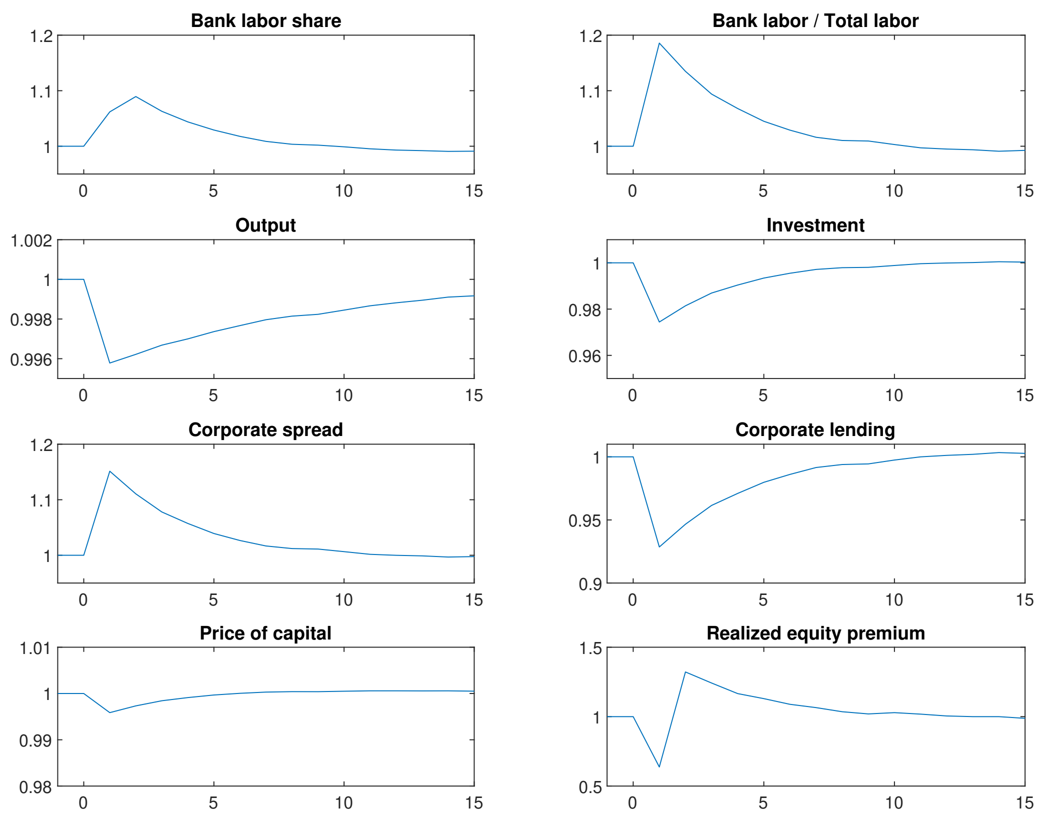


Figure B.4. Impulse responses to TFP shock in a model with credit risk

This figure plots the impulse response functions to a one standard deviation shock to TFP in a model with credit risk. To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the FLN shock at their average values. At $t = 1$, the FLN shock remains at its average value, but TFP falls unexpectedly. After $t = 1$, the FLN shock remains at its average value, while the TFP shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a low TFP, while $t > 1$ values are expected values.

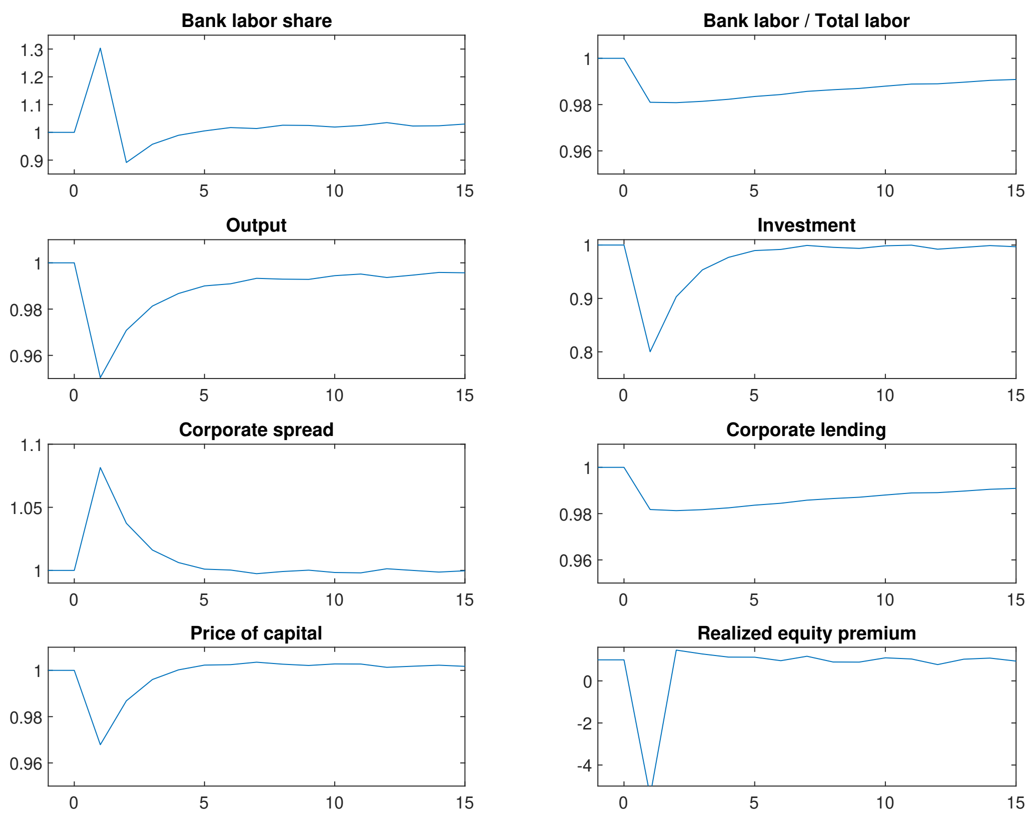


Figure B.5. Impulse responses to TFP shock in a model with wage rigidity

This figure plots the impulse response functions to a one standard deviation shock to TFP. It compares a model with wage rigidity ($\mu = 0.9$, solid blue line) to one without ($\mu = 0$, dashed red line). Both models have credit risk and do not have labor demand shocks ($\nu_{b,t}$ is a constant). To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the FLN shock at their average values. At $t = 1$, the FLN shock remains at its average value, but the TFP falls unexpectedly. After $t = 1$, the FLN shock remains at its average value, while the TFP shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a low TFP, while $t > 1$ values are expected values.

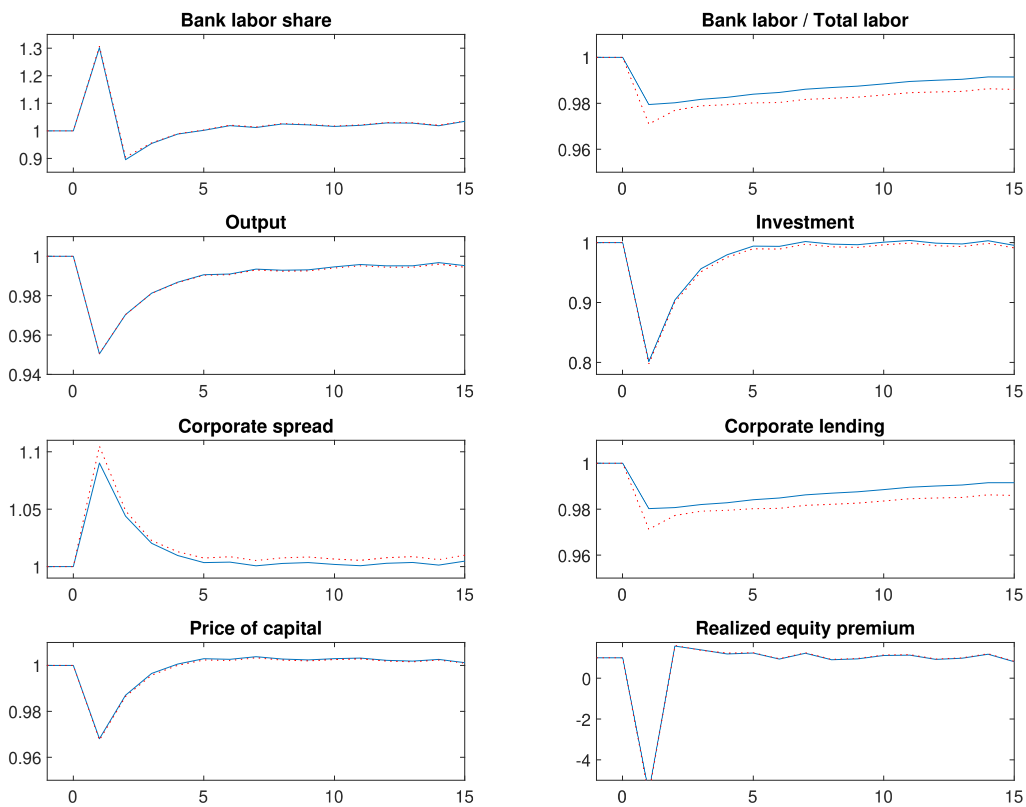


Figure B.6. Impulse responses to a credit shock

This figure plots the impulse response functions to a one standard deviation shock to the bank's maximum deposit to equity ratio κ. To produce the figure, we simulate the model for 50 periods, keeping both the TFP shock, and the credit shock at their average values. At $t = 1$, the TFP shock remains at its average value, but κ falls unexpectedly. After $t = 1$, the TFP shock remains at its average value, while κ varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a low TFP, while $t > 1$ values are expected values.

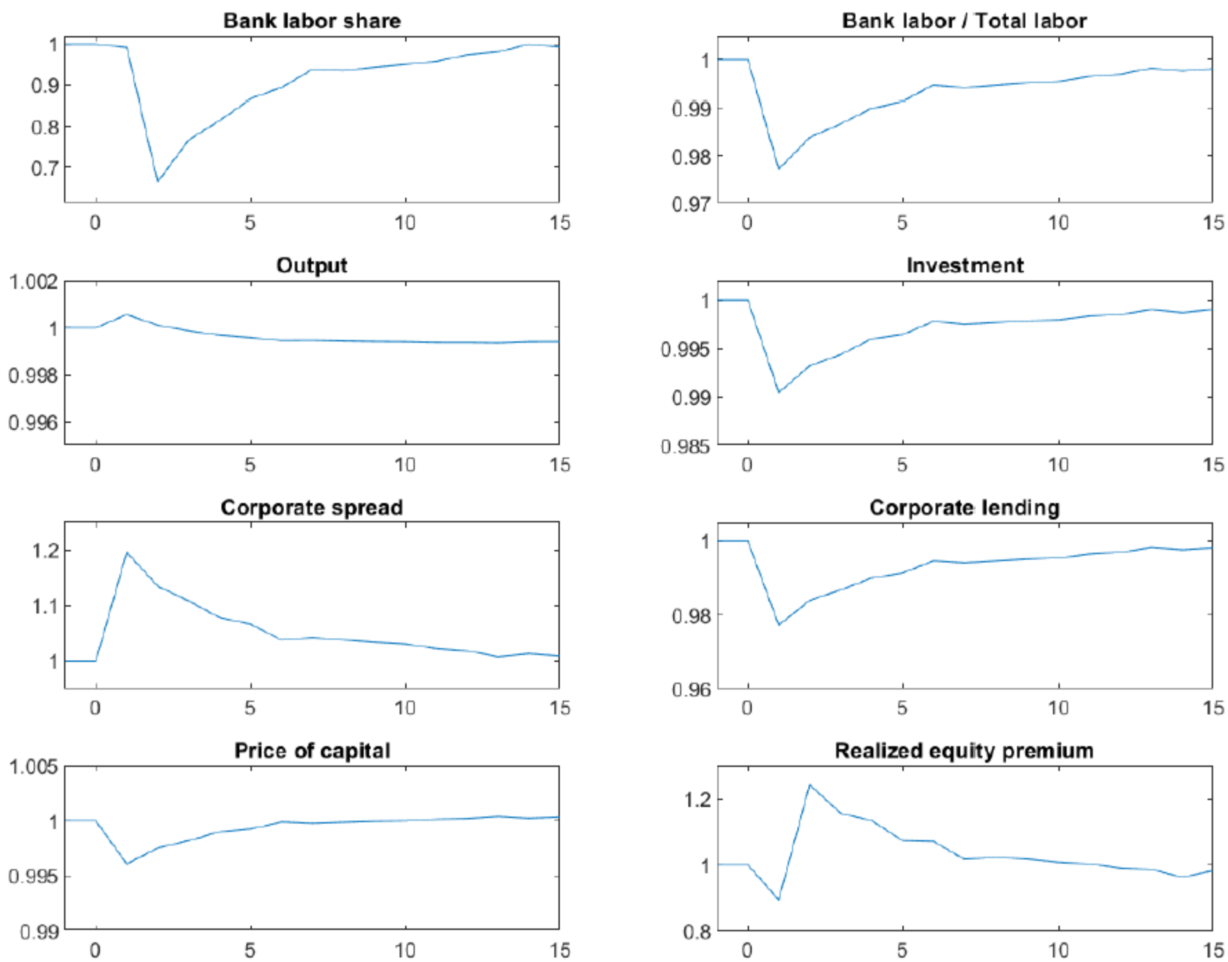


Figure B.7. Impulse responses to TFP shock in a model where bank labor is constant

This figure plots the impulse response functions to a one standard deviation shock to TFP in a model where there are no FLN shocks and where bank labor is set to be constant – this is a limiting case of infinite labor adjustment costs. To produce the figure, we simulate the model for 50 periods, keeping the TFP shock at its average value. At $t = 1$, the TFP falls unexpectedly. After $t = 1$, the TFP shock varies randomly. The figure reports the average financial sector labor share, aggregate output, aggregate investment, corporate spread, corporate lending, and the realized equity premium across many simulations. Note that the $t = 1$ values are realized value, conditional on a low TFP, while $t > 1$ values are expected values.

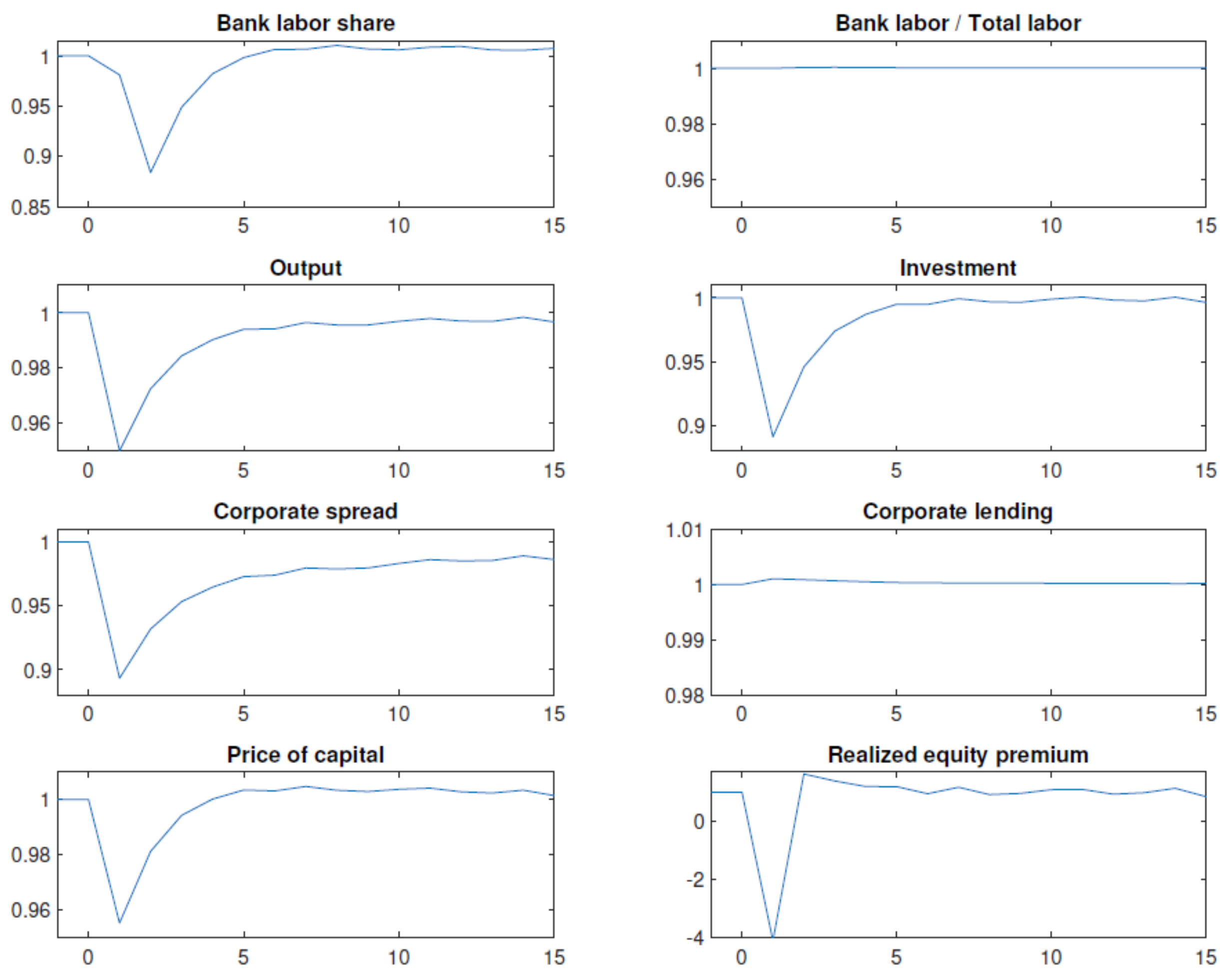
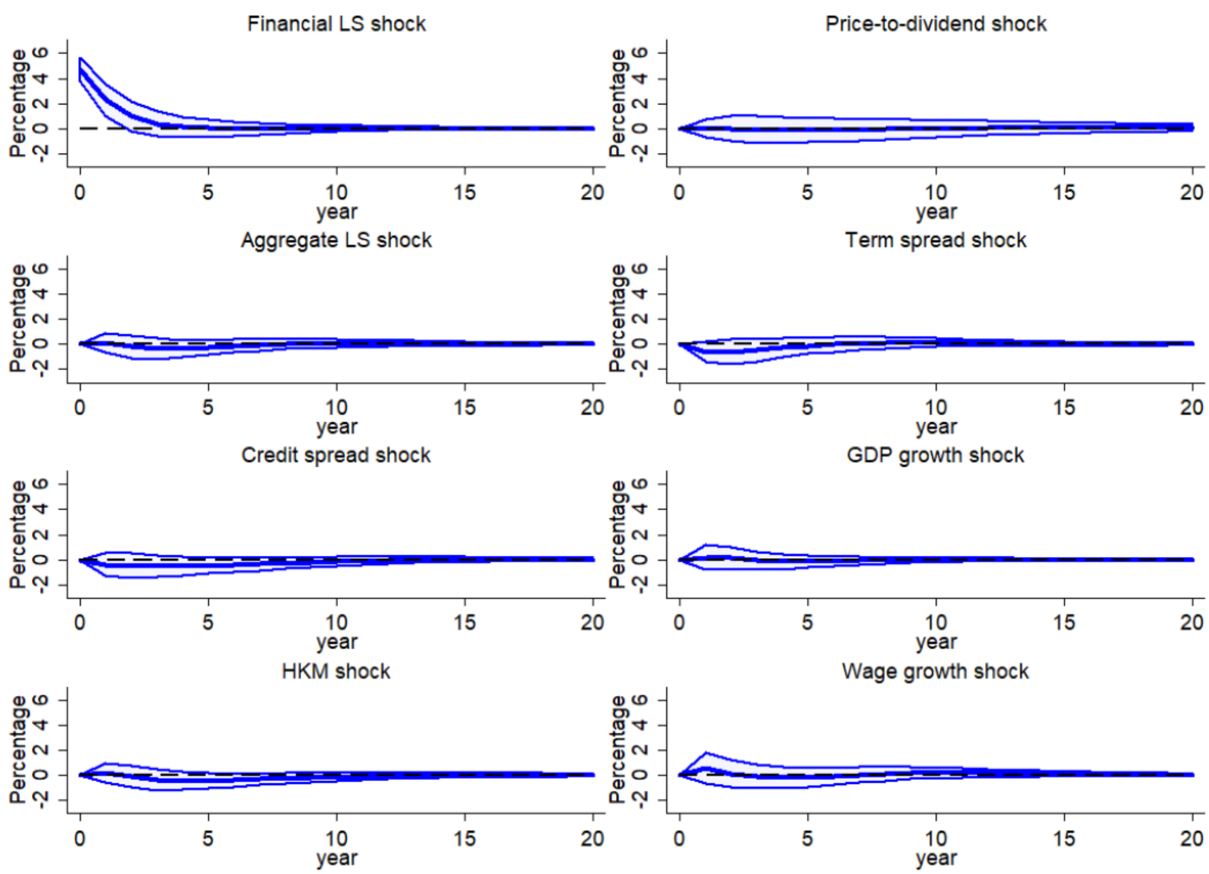


Figure B.8. Impulse responses of FLS from VAR

This figure plots the impulse response functions from a VAR(1) that includes FLS, GDP growth, wage growth, aggregate labor share, term spread, the price-to-dividend ratio, credit spread, and HKM. All the variables are expressed in percentages. The responses are drawn to one standard deviation of macro shocks.



Appendix C

Chapter Three Appendix

C.1 Technical Appendix

C.1.1 Model Relation: Random Search Market

In this section, we consider a variation on the simple model of Section 3.3.3 to allow the termination payoffs to be determined endogenously in a random search market governed by free entry across firms. In the market, unmatched specialists search costlessly and earn an unemployment benefit $B > 0$ and unmatched firms pay a flow cost $\Omega > 0$ to post a vacancy.

We begin with assumptions on how investors and specialists meet and how initial compensation is determined. Suppose that at some point in time there are v job vacancies and u unemployed specialists looking for jobs. The flow of contracts between firms and specialists is given by a matching technology $m(u,v)$, which we specialize to be homogeneous of degree one in u and v: $m(u,v) = u^{\phi}v^{1-\phi}$.

Because specialists (with constant a) and firms are identical, the arrival rates for unemployed specialists and firms with vacancies are then given by

$$\alpha_S = m(u,v)/u = (v/u)^{1-\phi} \text{ and } \alpha_F = m(u,v)/v = (v/u)^{-\phi},$$

where the ratio v/u is commonly referred to as market tightness.

Now when specialists and a firm meet, they bargain over specialists' initial compensation under a Nash bargaining protocol with threat points R_S and R_F:

$$W_0 \in_W (W - R_S)^{\theta}(P(N,W) - R_F)^{1-\theta},$$

where $\theta \in [0,1]$ is specialists' bargaining power.

The value of unemployment R_S and posting a vacancy R_F satisfy

$$\gamma R_S = B + \alpha_S(W_0 - R_S) \text{ and } rR_F = -\Omega + \alpha_F(P(N,W_0) - R_F). \tag{C.1}$$

Equilibrium and Solution

We simplify the model with homogeneity. In particular, we make the additional assumption that specialists' unemployment benefits scale with the intangible capital of their previous firm, $b = B/N$, and also depreciates at rate δ_N. The flow cost of posting a vacancy is also assumed to grow with the scale of the firm, $\omega = \Omega/N$, which also depreciates at rate δ_N. Larger firms presumably have more generous compensation packages for ex-employees and also the recruitment costs to find someone suitable for an important job also plausibly grow with firm scale.

We now discuss the computation of the equilibrium. First, free entry drives R_F to zero, so we rewrite the right equation of (C.1) under homogeneity as

$$\alpha_F p(w_0) = \omega.$$

The solution of the model involves the following steps

1. Guess $w = r_s \equiv R_S/N$
2. Solve for $p(w)$ from (3.12) on the space $w \in [w, \overline{w}]$ subject to the appropriate boundary and first-order conditions
3. Given r_s and $p(w)$ and using the three equations, $\alpha_F = \omega/p(w_0) = (v/u)^{-\phi}$, $\alpha_S = (v/u)^{1-\phi}$, and $r_s = (b + \alpha_S w_0)/(\alpha_S + \gamma)$, we solve for α_S, α_F, and w_0
4. Check w_0 satisfies $w_0 =_w (w - r_s)^{\theta} (p(w))^{1-\theta}$; if not, update the guess

As the solution shows, the lower bound w is endogenized by the frictions in the search market, the matching function, as well as the cost of vacancies and benefit of unemployment. We take the intricacy of this market as given, avoiding the difficulty of multiple equilibria arising in two-sided search models (see Burdett and Wright (1998) for discussion), and instead relying on our lower bound aw_0 and in particular a as a reduced-form device to capture these collective effect of these equilibrium forces.

C.1.2 Details of Computational Solution

We solve the partial differential equation in (3.21) with a finite difference method that approximates the function $p(a, w)$ on a two-dimensional non-rectangular grid: $a \in \{a_i(w_j)\}_{i=1}^{I^j}$ and $w \in \{w_j(a_i)\}_{j=1}^{J^i}$, where we define $\overline{w}(a_i) = w_{J^i}(a_i)$ and $\overline{a}(w_j) = a_{I^j}(w_j)$. Each set of grid points along j, $w_j(a_i)$, depend on the value of a_i, because of the boundary curve $\{\overline{w}(a_i)\}_{i=1}^{I}$. The set along i, $a_i(w_j)$ shares the same logic.

We approximate first derivatives of p using both backward and forward differences and second derivatives with central differences. All differences of a and w are calculated respectively over the fixed increments Δ_a and Δ_w. For the approximation of the derivatives at the boundaries, there are three different cases:

i. The boundary conditions of w imply that $p(a, 0) = l \Rightarrow p(a_i, a_i w_0) \approx l$ and $p_w(a, \overline{w}(a)) = -1 \Rightarrow p(a_i, w_{J^i+1}) \approx p(a_i, w_{J^i}) - \Delta_w$ under a forward difference, where both conditions hold for all i.
ii. The boundary conditions of a imply that $p_a(\overline{a}(w), w) = -1 \Rightarrow p(a_{I^j+1}, w_j) \approx p(a_{I^j}, w_j) - \Delta_a$ under a forward difference, where both conditions hold for all j.
iii. The boundary conditions along the joint upper boundary where $p_{aw}(\overline{a}(w), \overline{w}(a)) = 0$ for all $\overline{a}(w)$ and $\overline{w}(a)$ implies

$$p(a_{I^j+1}, w_{J^i+1}) \approx p(a_{I^j+1}, w_{J^i}) - \Delta_w \approx p(a_{I^j}, w_{J^i}) - \Delta_w - \Delta_a.$$

We describe our computational algorithm below:

1. Guess the value of $p^b(\cdot)$ on the two-dimensional non-rectangular grid: $a \in \{a_i\}_{i=1}^{I^j}$ and $w \in \{w_j(a_i)\}_{j=1}^{J^i}$ and approximate the derivatives,
2. Calculate the investment policy function in (3.22),

3. We update the value function through an implicit method that solves the vector $p^{b+1} = (p^{b+1}_{1,1}, \ldots, p^{b+1}_{1,J^1}, p^{b+1}_{2,1}, \ldots, p^{b+1}_{2,J^2}, \ldots, p^{b+1}_{I^J,J^I})'$ with notation $p_{i,j} = p(a_i, w_j)$. It begins with a guess $b = 1$ and proceeds to iterate until convergence ($\max(|p^{b+1} - p^b|) < 10^{-9}$) on the value function

$$p^{b+1}\left[\left(\frac{1}{\Delta} + r - (g - \delta_N)\right) - \mathbf{Q}\right] = p^b/\Delta + D, \tag{C.2}$$

4. After convergence, check to see if the boundaries in (3.14), (3.15), (3.17), (3.18), and (3.19) are numerically satisfied; if not, then update the shape of the non-rectangular grid. We report statistics on the numerical accuracy of these boundaries in Table C.7.

During each iteration of (C.2), g is calculated from step 2, $\Delta > 0$ is the step size of the iterative method, and $\mathbf{Q}$ is the transition matrix defined by the diffusion processes of the states a and w and the boundaries described above

$$\mathbf{Q} = \begin{bmatrix}
q^{ss}_{1,1} & q^{su}_{1,1} & 0 & \cdots & 0 & q^{us}_{1,1} & 0 & 0 & \cdots & 0 & \cdots & 0 \\
q^{sd}_{1,2} & q^{ss}_{1,2} & q^{su}_{1,2} & \ddots & \vdots & 0 & q^{us}_{1,2} & 0 & \ddots & \vdots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\
0 & \cdots & \cdots & q^{sd}_{1,J^1} & q^{ss}_{1,J^1} & 0 & \cdots & \cdots & 0 & q^{us}_{1,J^1} & \ddots & \vdots \\
q^{ds}_{2,1} & 0 & 0 & \cdots & 0 & q^{ss}_{2,1} & q^{su}_{2,1} & 0 & \cdots & 0 & \ddots & \vdots \\
0 & q^{ds}_{2,2} & 0 & \ddots & \vdots & q^{sd}_{2,2} & q^{ss}_{2,2} & q^{su}_{2,2} & \ddots & \vdots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \ddots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\
0 & \cdots & \cdots & 0 & q^{ds}_{2,J^2} & 0 & \cdots & \cdots & q^{sd}_{2,J^2} & q^{ss}_{2,J^2} & \ddots & \vdots \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & q^{sd}_{I^J,J^I} & q^{ss}_{I^J,J^I}
\end{bmatrix}.$$

Adjustments to transition rates along the boundaries are made to $\mathbf{Q}$ for the non-rectangular grid as it is an approximation and ensure that the non-termination-boundary rows of the transition matrix $\mathbf{Q}$ sum to zero. The termination-boundary rows do not sum to zero as they measure the (absorbing) exiting mass of firms. The transition matrix $\mathbf{Q}$ is the discretized analogy of the infinitesimal generator of (da_t, dw_t): $\mathcal{A}\vartheta(a,w)$ for some arbitrary function $\vartheta(\cdot)$. The elements of $\mathbf{Q}$ are based on an upwind scheme and defined as

- $q^{ss}_{i,j} = -\max(\mathbb{E}_t[dw],0)/\Delta_w + \min(\mathbb{E}_t[dw],0)/\Delta_w - \max(\mathbb{E}_t[da],0)/\Delta_a + \min(\mathbb{E}_t[da],0)/\Delta_a - \mathbb{E}_t[dw^2]/\Delta_w^2 - \mathbb{E}_t[da^2]/\Delta_a^2$
- $q^{su}_{i,j} = \max(\mathbb{E}_t[dw],0)/\Delta_w + \mathbb{E}_t[dw^2]/(2\Delta_w^2)$
- $q^{sd}_{i,j} = -\min(\mathbb{E}_t[dw],0)/\Delta_w + \mathbb{E}_t[dw^2]/(2\Delta_w^2)$
- $q^{us}_{i,j} = \max(\mathbb{E}_t[da],0)/\Delta_a + \mathbb{E}_t[da^2]/(2\Delta_a^2)$
- $q^{ds}_{i,j} = -\min(\mathbb{E}_t[da],0)/\Delta_a + \mathbb{E}_t[da^2]/(2\Delta_a^2)$

where the conditional moments of state variables are $\mathbb{E}_t[dw] = (\gamma - (g - \delta_N))w$, $\mathbb{E}_t[da] = \kappa a(g - \delta_N)$, $\mathbb{E}_t[dw^2] = \sigma_N^2(\lambda - w)^2$ and $\mathbb{E}_t[da^2] = \sigma_a^2 a^2$.

Lastly, the vector of constants D required by the boundaries takes the form

$$D = Z - c(g_{i,j}) + \begin{bmatrix} q^{sd}_{1,1} \times l \\ \vdots \\ (q^{su}_{1,J^1}) \times (-\Delta_w) \\ q^{sd}_{2,1} \times l \\ \vdots \\ (q^{su}_{2,J^2}) \times (-\Delta_w) \\ \vdots \\ \vdots \\ (q^{su}_{I^J,J^I}) \times (-\Delta_w) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ (q^{us}_{I^1,1}) \times (-\Delta_a) \\ \vdots \\ \vdots \\ (q^{us}_{I^J,J^I}) \times (-\Delta_a) \end{bmatrix},$$

and intuitively captures the firm profit, $Z - c(g_{i,j})$, where $i = 1,..,I^j$ and $j = 1,..,J^i$, the rates of cash outflows from payments to specialists, $-\Delta_w$ and $-\Delta_a$, and liquidation, l.

Convergence to the unique solution is assured by Barles and Souganidis (1991) (see Achdou et al. (2022) for discussion). They show that if the solution method satisfies monotonicity, stability, and consistency, then as Δ_a and Δ_w get small the solution converges locally uniformly to the unique viscosity solution. Here, monotonicity is ensured by the upwind scheme; stability, by the implicit method (on a uniformly bounded value function that is independent of Δ_a and Δ_w); and consistency, by the backwards time-step of the iterative method.

C.1.3 Optimality

Define the gain process $\{G\}$ under any incentive-compatible contract $C = (g, U, \tau)$ for any $t < \tau$ as

$$G_t(C) = \int_0^t e^{-rs}(\Pi_s ds - dU_s) + e^{-rt} P(a_t, N_t, W_t),$$

where N_t, a_t, and W_t follow (3.2), (3.3), (3.5), respectively. Homogeneity and Ito's lemma imply

$$e^{rt} dG_t = N_t \left\{ \begin{array}{c} \left[\begin{array}{c} -rp + Z - c(g_t) + p(g_t - \delta_N) + p_w(\gamma - (g_t - \delta_N))w_t + \frac{1}{2} p_{ww} \left((\beta_t - w_t)\sigma_N \right)^2 \\ + p_a \kappa (g_t - \delta_N) a + \frac{1}{2} p_{aa} a^2 \sigma_a^2 \end{array} \right] dt \\ -(1 + p_w) du_t + (p + p_w(\beta_t - w_t))\sigma_N dB_t \end{array} \right\},$$

where $p(\cdot)$'s dependence on states (a_t, w_t) and $G(\cdot)$'s dependence on a contract C have been henceforth omitted for conciseness.

Under the optimal investment $g^\star$ and incentive policies $\beta_t^\star = \lambda$, the top two lines in the square brackets are the optimized PDE in (3.21) and therefore zero. For models in which the only state variable is agents' continuation utility this nonpositivity condition follows from the concavity of $p(w)$. In this more general case, we verify numerically that for any other incentive compatible policy both p_{ww} and $\beta p_{ww}/2 + p_{aw}$ under the policy with the smallest β are nonpositive. We depict both conditions density-weighted and conditional on w in Panel A of Figure C.1.

The term capturing the optimality of the continuation payment policy, $-(1 + p_w)dU_t$, is non-positive since $p_w \geq -1$ but equals zero under the optimal contract. Therefore, for the auxiliary gain process we have

$$dG_t = \mu_G(t)dt + e^{-rt} N_t (p + p_w(\beta_t - w_t))\sigma_N dB_t$$

where $\mu_G(t)dt \leq 0$. Let $\varphi_t \equiv e^{-rt}N_t(p + p_w(\beta_t - w_t))\sigma_N$. We impose the usual regularity conditions to ensure that $\mathbb{E}\left[\int_0^T \varphi_t dB_t\right] = 0$ for all $T \geq 0$. This implies that $\{G\}$ is a supermartingale.

Now we can evaluate the investor's payoff for an arbitrary incentive compatible contract. Recall that $P(a_\tau; N_\tau; W_\tau) = lN_\tau$. Given any $t < \infty$,

$$
\begin{aligned}
&\mathbb{E}\left[\int_0^\tau e^{-rt}(\Pi_t dt - dU_t) + e^{-r\tau} lN_\tau\right] \\
=&\mathbb{E}\left[G_{t\wedge\tau} + 1_{t\leq\tau}\left(\int_t^\tau e^{-rs}(\Pi_s ds - dU_s) + e^{-r\tau} lN_\tau - e^{-rt}P(a_t, N_t, W_t)\right)\right] \\
=&\mathbb{E}\left[G_{t\wedge\tau}\right] + e^{-rt}\mathbb{E}\left[1_{t\leq\tau}\left(\mathbb{E}_t\left[\int_t^\tau e^{-r(s-t)}(\Pi_s ds - dU_s) + e^{-r(\tau-t)} lN_\tau\right]\right) - P(a_t, N_t, W_t)\right] \\
\leq& G_0 + (q^{FB} - l)\mathbb{E}[e^{-rt}N_t]
\end{aligned}
$$

Here we use the notation $t \wedge \tau = \min\{t, \tau\}$. The first term of the inequality follows from the nonpositive drift of dG_t and the martingale property of $\int_0^{t\wedge\tau} \varphi_s dB_s$. The second term follows from

$$
\mathbb{E}_t\left[\int_t^\tau e^{-r(s-t)}(\Pi_s ds - dU_s) + e^{-r(\tau-t)} lN_\tau\right] \leq q^{FB}N_t - w_t N_t
$$

which is the first-best result and

$$
q^{FB}N_t - w_t N_t - P(a_t, N_t, W_t) \leq (q^{FB} - l)N_t
$$

We impose the standard transversality condition $\lim_{T\to\infty}\mathbb{E}[e^{-rT}N_T] = 0$. Let $t \to \infty$

$$
\mathbb{E}\left[\int_0^\tau e^{-rt}(\Pi_t dt - dU_t) + e^{-r\tau} lN_\tau\right] \leq G_0
$$

for all incentive-compatible contracts. On the other hand, under the optimal contract $C^\star$, investor's payoff $G(C^\star)$ achieves G_0 because the above weak inequality holds with equality when $t \to \infty$.

Full-Effort Condition

In the full-effort case, we require the rate of private benefits $\lambda g_t N_t dt$ to be sufficiently small to ensure the optimality of $e_t = 1$ is implemented all the time. If specialists' shirked ($e_t = 0$), intangible capital would evolve as

$$
dN_t = -\delta_N N_t dt + \sigma_N N_t dB_t,
$$

and their continuation payoff would change according to

$$
dW_t = \gamma W_t dt - \lambda\widehat{g}_t N_t dt + \widehat{\beta}_t N_t \sigma_N dB_t,
$$

where $\widehat{g}_t$ and $\widehat{\beta}_t$ are the chosen investment rate and incentive coefficient under the shirking policy.

For full effort ($e_t = 1$) to remain optimal, we need investors' payoff rate from allowing agents to shirk to be lower than under the optimal contract. Equivalently, investors' optimal gain process needs to remain a supermartingale with respect to this shirking policy:

$$rp \geq Z - c(\widehat{g}) - \delta_N p + p_w((\gamma+\delta_N)w_t - \lambda\widehat{g}) + \frac{1}{2}p_{ww}(\widehat{\beta}-w)^2\sigma_N^2$$
$$+ p_a\kappa(\widehat{g}-\delta_N)a + \frac{1}{2}p_{aa}a^2\sigma_a^2, \text{ for all } a \text{ and } w,$$

where we omit $p(\cdot)$'s dependence on states for brevity.

Because $p(\cdot)$ is concave in w, it is optimal to set the incentive coefficient to w: $\widehat{\beta}_t = w_t$ for all t. Since investment is unproductive when agents shirk, it is also optimal to set it to zero: $\widehat{g}_t = 0$.

Under these choices, the following equation must be satisfied for full effort to remain the optimal solution at all times:

$$rp \geq Z - c(0) - \delta_N p + p_w((\gamma+\delta_N)w) - p_a\kappa\delta_N a + \frac{1}{2}p_{aa}a^2\sigma_a^2, \text{ for all } a \text{ and } w.$$

We plot this weakly positive condition as a density-weighted function conditional on w in Panel B of Figure C.1.

C.2 Empirical Appendix

We use all industrial, standard format, consolidated accounts of firms in Compustat. We exclude all utility (SIC 4900-4999) and financial (SIC 6000-6999) firms and those missing assets (at) or sales ($sale$). We retain only those listed on the AMEX, NASDAQ, or NYSE.

C.2.1 Variable Definitions

- Age Indicator = 1 if CEO is over 62 years old and 0 otherwise
- Cash-to-Capital = Cash (che) / Intangible Capital
- Intangible Capital = see equation (3.27)
- Leverage = Total Debt ($dltt + dlc$) / Intangible Capital
- Market Equity = Price per Share × Shares Outstanding (December values of abs(prc) × shrout from CRSP)
- Profitability = (EBIT (ebit(t)) - Physical Capital Investment (capx(t))) / Intangible Capital (N(t-1))
- Tobin's Q = (Market Equity ($prcc_f \times csho$) + Long-term Debt ($dltt$) + $tdc1$/0.11) / Intangible Capital, where 0.11 is the calibrated value of γ in Table 3.4.
- Turnover = 1 if CEO leaves firm in a given year and 0 otherwise

Figure C.1. Optimality and Full Effort Conditions

The top panel depicts the non-positivity condition required for optimality. The bottom panel shows that the full effort condition ($e_t = 1$ for all t) is optimal. Both figures depict conditional densities.

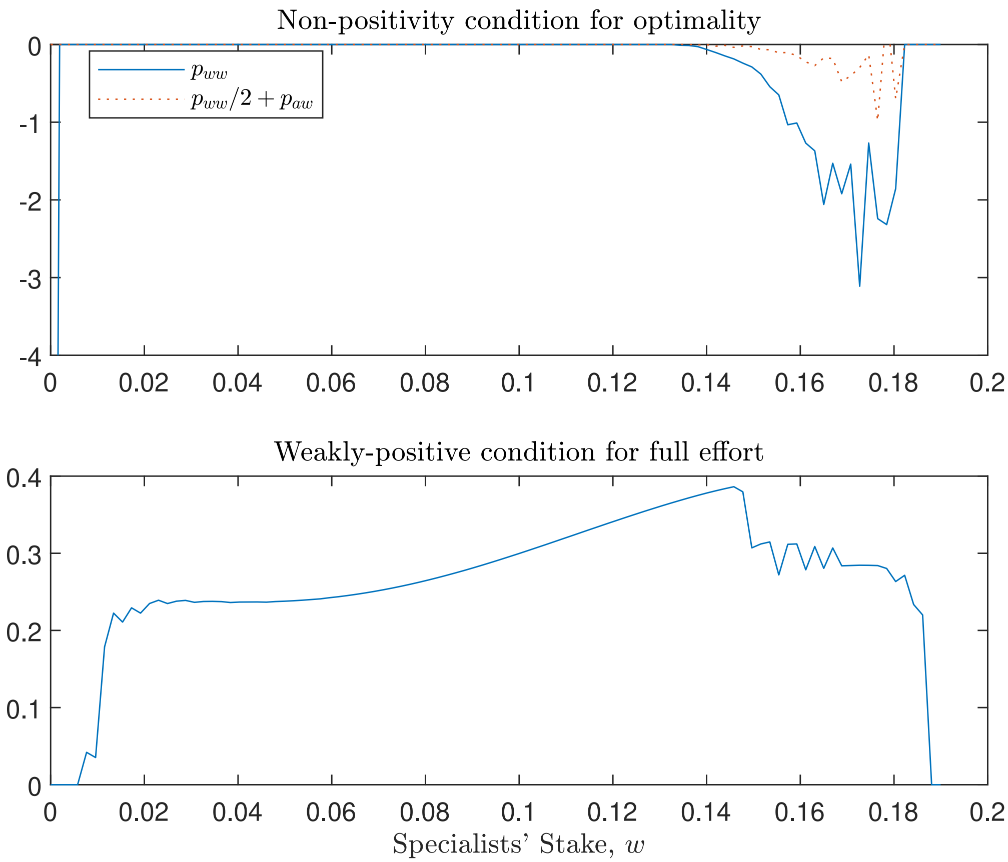


Table C.1. Summary Statistics

Panel A of this table provides the summary statistics of the main variables in the empirical analysis. *Age Indicator* takes a value of one if the firm's CEO is over 62 years old, and is lagged. *Cash* is the lagged ratio of cash to intangible capital. *Intangible Capital* is from (3.27) and is the level of intangible capital for a firm in a given year, in millions of real 1982 dollars. *Investment Rate* is the investment rate of intangible capital for a firm in a given year. *R&D Investment* is R&D expenditure scaled the intangible capital. *Leverage* is the lagged ratio of total debt to intangible capital. *NCEI* is the non-compete enforceability index. Δ*NCEI* takes a value of one if the firm's state's *NCEI* is higher in a given year than the 1992 initial value, negative one if it is lower, and zero if it is the same. *Outside Option* is the outside option value for a given firm's CEO in a given year (in millions of 1982 dollars). *Profitability* is the lagged ratio of after-tax EBITDA net of physical capital investment to intangible capital. *Tobin's Q* is the lagged sum of market equity, long-term debt and the stock of CEO compensation to intangible capital. *Turnover* is an indicator that takes a value of one if the firm has CEO turnover in a given year and zero otherwise. Panel B provides the correlation matrix between changes in the NCEI, Δ*NCEI*, and changes in aggregate factors which include: the percentage change in real GDP, the percentage change in the unemployment rate, the percentage change in real consumption, and the percentage change in the Fed Funds Rate. All data items are from the St. Louis Federal Reserve's FRED database.

Panel A: Summary Statistics						
	N	Mean	Std	P25	P50	P75
Age Indicator	20,468	0.171	0.376	0	0	0
Cash	20,468	0.748	1.534	0.085	0.274	0.733
Intangible Capital	20,468	8.197	23.872	0.778	1.986	5.941
Investment Rate	20,468	0.212	0.113	0.149	0.194	0.250
R&D Investment	20,468	0.090	0.146	0.000	0.017	0.127
Leverage	20,468	1.955	5.221	0.096	0.510	1.430
NCEI	20,468	4.094	2.223	3	5	5
ΔNCEI	20,468	0.006	0.399	0	0	0
log Outside Option	20,468	0.946	0.456	0.691	0.987	1.224
$\frac{\text{Outside Option}}{\text{Intangible Capital}}$	20,468	0.020	0.043	0.002	0.007	0.019
Profitability	20,468	0.042	1.465	-0.003	0.135	0.322
Tobin's *Q*	20,468	11.167	23.606	2.471	4.717	9.582
Turnover	20,468	0.047	0.213	0	0	0

Panel B: Correlation Between NCEI and Aggregate Outcomes				
	%ΔReal GDP	%ΔUnemployment Rate	%ΔReal Consumption	%ΔFed Funds Rate
ΔNCEI	0.0215	-0.1563	0.0200	0.0105

Table C.2. Reduced Form: NCEI on Investment and Turnover

This table provides reduced-form estimates for the effect of the NCEI on intangible investment and CEO turnover. *NCEI* is the non-compete enforceability index. Δ*NCEI* takes a value of one if the firm's state's *NCEI* is higher in a given year than the 1992 initial value, negative one if it is lower, and zero if it is the same. Intangible Investment Rate is the investment rate of intangible capital in a given year. R&D Investment is R&D expenditures scaled by intangible capital. CEO Turnover is one if the company has a CEO turnover and zero otherwise. Control variables are all lagged and include: investment rate, turnover, Tobin's Q, cash, profitability, leverage, the logged level of intangible capital, and a CEO indicator for whether her/his age is above 62. Firm fixed effects and year fixed effects are included. Observations are at the firm-year level. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Variable:	(1) Intangible Investment Rate	(2) Intangible Investment Rate	(3) R&D Investment	(4) R&D Investment	(5) CEO Turnover	(6) CEO Turnover
NCEI	0.003**		0.007***		−0.007*	
	(0.00)		(0.00)		(0.00)	
Δ*NCEI*		0.004**		0.009***		−0.012**
		(0.00)		(0.00)		(0.01)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	20,316	20,316	20,316	20,316	20,316	20,316

Table C.3. Falsification Test for the Timing of NCEI Changes

This table provides a falsification test for the year of changes in the NCEI. $\Delta NCEI_{false}$ sets the change defined by $\Delta NCEI$ to falsely occur 5 years before the actual change in the NCEI. Intangible Investment Rate is the investment rate of intangible capital in a given year. R&D Investment is R&D expenditures scaled by intangible capital. CEO Turnover is one if the company has a CEO turnover and zero otherwise. Control variables are all lagged and include: investment rate, turnover, Tobin's Q, cash, profitability, leverage, the logged level of intangible capital, and a CEO indicator for whether her/his age is above 62. Firm fixed effects and year fixed effects are included. Observations are at the firm-year level. Column (1) provides first-stage estimates, while columns (2)-(4) provides second-stage estimates. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Variable:	$\log$ Outside Option	Intangible Investment Rate	R&D Investment	CEO Turnover
$\Delta NCEI_{false}$	−0.017			
	(0.01)			
$\log \widehat{\text{Outside Option}}$		−0.224	−0.062	0.487
		(0.30)	(0.22)	(0.67)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	11,041	11,041	11,041	11,041

Table C.4. Cumulative Intangible Investment Rates

This table provides the empirical results of CEO outside options on cumulative intangible investment rates. Panel A provides the results instrumented by $NCEI$, while Panel B provides the results instrumented by $\Delta NCEI$. $Inv\,Rate_{t,t+k}$ is the cumulative investment rate from year t to $t+k-1$, defined as

$$Inv\,Rate_{t,t+k} = \left(Inv_t^N + Inv_{t+1}^N .. + Inv_{n+k-1}^N\right)/N_{t-1},$$

where Inv_t^N is the intangible capital investment in year t. Control variables are all lagged and include: investment rate, turnover, Tobin's Q, cash, profitability, leverage, the logged level of intangible capital, and a CEO indicator for whether her/his age is above 62. Firm fixed effects and year fixed effects are included. Observations are at the firm-year level. Standard errors are clustered at the firm level and are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Instrumented by $NCEI$				
	(1)	(2)	(3)	(4)
Dep. Variable:	$Inv\,Rate_{t,t+k}$			
Lags (k):	2	3	4	5
$\log \widehat{\text{Outside Option}}$	−0.237**	−0.505**	−0.745*	−0.759
	(0.12)	(0.25)	(0.41)	(0.55)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	19,485	18,619	17,823	17,051

Panel B: Instrumented by $\Delta NCEI$				
	(1)	(2)	(3)	(4)
Dep. Variable:	$Inv\,Rate_{t,t+k}$			
Lags (k):	2	3	4	5
$\log \widehat{\text{Outside Option}}$	−0.210**	−0.446**	−0.627*	−0.541
	(0.11)	(0.22)	(0.35)	(0.45)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	19,485	18,619	17,823	17,051

Table C.5. Effect of Outside Options on CEO Mobility

This table provides the empirical results for the effect of outside options on CEO mobility. Following Graham et al. (2020), for each firm i in industry j, mobility is measured as the fraction of CEOs in industry j leaving their offices in year t and finding another executive job within 2 years ($\text{Mobility}_{t,t+2}$), 5 years ($\text{Mobility}_{t,t+5}$) or ultimately in our sample (Mobility). The other details are the same as Panel A of Table 3.2. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Instrument: *NCEI*			Instrument: Δ*NCEI*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	$\text{Mobility}_{t,t+2}$	$\text{Mobility}_{t,t+5}$	Mobility	$\text{Mobility}_{t,t+2}$	$\text{Mobility}_{t,t+5}$	Mobility
$\log \widehat{\text{Outside Option}}$	0.167***	0.296***	0.333***	0.043	0.209**	0.250***
	(0.06)	(0.08)	(0.09)	(0.07)	(0.08)	(0.09)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	20,316	20,316	20,316	20,316	20,316	20,316

Table C.6. Instrumented Effect of Non-Compete Enforcement on Entry and Exits

This table provides the empirical results for the effect of outside options on firm entries and exits. Panel A measures the entries and exits of public firms, and Panel B measures those for both public and private firms using data from Business Dynamics Statistics of Census Bureau. In Panel A, $\log \text{Entry}$ is the logged yearly number of new Compustat firms in state s and industry j. In Panel B, $\log \text{Entry}$ is the logged yearly number of new establishments from BDS in state s and industry j. In Panel A, $\log \text{Exits}$ is the logged yearly number of Compustat firm exits in state s and industry j. In Panel B, $\log \text{Entry}$ is the logged yearly number of closed establishments from BDS in state s and industry j. Observations are at the state-industry-year level. Control variables are all lagged and include: Herfindahl-Hirschman Index, number of firms, and average firm age. $State \times Industry$ fixed effects and $Industry \times Year$ fixed effects are included. Standard errors are clustered at the state level and t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Compustat Firms

	Instrument: *NCEI*		Instrument: Δ*NCEI*	
	(1)	(2)	(3)	(4)
Dep. Variable:	$\log \text{Entry}$	$\log \text{Exits}$	$\log \text{Entry}$	$\log \text{Exits}$
$\log \widehat{\text{Outside Option}}$	0.626	0.322**	0.445	0.228
	(0.52)	(0.13)	(0.34)	(0.20)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	10,251	10,251	10,251	10,251

Panel B: BDS Firms

	Instrument: *NCEI*		Instrument: Δ*NCEI*	
	(1)	(2)	(3)	(4)
Dep. Variable:	$\log \text{Entry}$	$\log \text{Exits}$	$\log \text{Entry}$	$\log \text{Exits}$
$\log \widehat{\text{Outside Option}}$	−1.124	−0.188	−1.008*	−0.346
	(0.82)	(0.40)	(0.55)	(0.42)
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	10,120	10,120	10,120	10,120

Table C.7. Statistics of Model Boundary Conditions

This table provides the mean and the median across a of the following boundary conditions: smooth pasting $p_w(a,\overline{w}(a)) = -1$, super contact $p_{ww}(a,\overline{w}(a)) = 0$, and the lower boundary $p(a,w(a)) - l = 0$.

	Smooth Pasting $p_w(a,\cdot)$	Super Contact $p_{ww}(a,\cdot)$	Lower Boundary $\lvert p(a,\cdot) - l \rvert$
Mean	−1.051	−7.423	0.075
Median	−1.004	0	0.067