Essays on Empirical Asset Pricing

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Dedication

This dissertation is dedicated to my wife and my parents - for their love, care and support.

Abstract

My dissertation investigates the interaction between macroeconomy and asset prices. On one hand, asset returns can be explained by the riskiness embedded in the economic variables; on the other hand, the aggregate economy is affected by the appropriate distribution of productive resources, arising from firm's financing capability. My dissertation contains two chapters which study these two questions respectively.

Chapter one explores the role of investor sentiment in the pricing of a broad set of macro-related risk factors. Economic theory suggests that pervasive factors (such as market returns and consumption growth) should be priced in the cross-section of stock returns. However, when we form portfolios based directly on their exposure to macro-related factors, we find that portfolios with higher risk exposure do not earn higher returns. More important, we discover a striking two-regime pattern for all 10 macro-related factors: high-risk portfolios earn significantly higher returns than low-risk portfolios following low-sentiment periods, whereas the exact opposite occurs following high-sentiment periods. We argue that these findings are consistent with a setting in which market-wide sentiment is combined with short-sale impediments and sentiment-driven investors undermine the traditional risk-return tradeoff, especially during high-sentiment periods.

Chapter two studies capital misallocation and its implication on output losses. Financial market frictions may lead to capital misallocation and, thus, reduce the aggregate output. This paper empirically quantifies the fraction of total factor productivity (TFP) loss that is attributable to financial frictions. A simple model is set up to map the dispersion in firm's borrowing costs into TFP loss. Equity cost of capital contains information of firm's expected profitability; and, is used as a proxy for firm's borrowing cost. I find that the misallocation due to financial frictions can reduce TFP by a magnitude from 3.2% to 6.4%. TFP losses can be stronger during times when credit is tightening and among firms that have more severe financial constraints. The time series of TFP losses is countercyclical, which suggests more heterogeneity in firm's borrowing costs during the recession. The paper also shows that Hsieh and Klenow (2009) may overstate the output loss caused by the misallocation which is attributable to financial frictions.

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Chapter 1

Investor Sentiment and Economic Forces

1.1 Introduction

Economic theory (e.g., Merton's (1973) ICAPM) suggests that innovations in pervasive macro-related variables are risk factors that should be priced in the stock market. This study explores the pricing of macro factors in the cross section of stock returns. We construct portfolios by sorting individual stocks directly on their sensitivity to a broad set of macro-related factors. This approach provides a natural way to produce portfolios with different exposure to underlying factors. Thus, we believe that these beta-sorted portfolios are particularly well suited for the study of the pricing of macro risk factors.

We consider a large set of macro-related factors: consumption growth, industrial production growth, total factor productivity (TFP) growth, innovations in inflation, changes in expected inflation, the term premium, the default premium, the innovation in aggregate market volatility, aggregate market excess returns, and labor income growth. For each risk factor, we examine the strategy that goes long the stocks in the highest-risk decile and short those in the lowest-risk decile. Overall, we find that the spread between high- and low-risk portfolios is close to zero (0.03% per month) and insignificant, lending no support standard economic theory.[1]

Using the market-wide sentiment index constructed by Baker and Wurgler (2006), we explore sentiment-related mispricing as at least a partial explanation for the apparent empirical failure of economic theory. Whether investor sentiment affects stock prices has been a question of long-standing interest to economists. In standard economic models, investor sentiment does not play a role in asset prices. Researchers in behavioral finance, in contrast, suggest that when arbitrage is limited, noise trader sentiment can persist in financial markets and affect asset prices (e.g., Delong, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997)).

Specifically, following Stambaugh, Yu, and Yuan (2011), we investigate the hypotheses that result from combining two prominent concepts in the literature. The first concept is that investor sentiment contains a time-varying market-wide component that could affect prices on many securities in the same direction at the same time.[2] The second concept is that impediments to short selling play a significant role in limiting the ability of rational traders to exploit overpricing.[3] Combining these two concepts, it

[1]One might argue that there are a lot of noises in beta estimations. Thus, it is not very surprising that return spreads between high- and low-risk firms are not significant. We are very sympathetic to this measurement error view. However, as we discuss in more detail later, our main results on the two-regime pattern are not subject to this criticism. Actually, potential measurement errors should weaken the two-regime pattern we document below.

[2]Studies addressing market-wide sentiment, among others, include Delong, et al. (1990), Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Vishny (1998), Brown, and Cliff (2004, 2005), Baker and Wurgler (2006, 2007, 2011), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), Frazzini and Lamont (2008), Kaniel, Saar, and Titman (2008), Livnat and Petrovic (2008), Antoniou, Doukas, and Subrahmanyam (2010), Gao, Yu, and Yuan (2010), Hwang (2011), Baker, Wurgler, and Yuan (2011), Yu and Yuan (2011), Stambaugh, Yu, and Yuan (2011), Chung, Hung, and Yeh (2011), and Yu (2013).

[3]Notable papers exploring the role of short-sale constraints in asset prices include Figlewski (1981), Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), Duffie, Garleanu and Pedersen (2002), Jones and Lamont (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), Lamont and Stein (2004), Ofek, Richardson, and Whitelaw (2004), and Nagel (2005).

follows that there are potentially many overpriced assets during high-sentiment periods. However, asset prices should be close to their fundamental value during low-sentiment periods, since underpricing can be counterveiled by arbitrageur, and pessimists tend to stay out of markets due to short-sale impediments. As a result, the market tends to be more rational and efficient during low-sentiment periods than during high-sentiment periods, and hence the first testable hypothesis regarding macro-related factors is that firms with high risk should earn higher returns than firms with low risk during low-sentiment periods.

Our second hypothesis is that during high-sentiment periods, the return spread between high- and low-risk portfolios should be smaller than that during low-sentiment periods and could potentially be negative. This hypothesis follows for at least two reasons. First, during high-sentiment periods, sentiment-driven investors tend to require a smaller compensation for the risk they bear, probably due to effectively lower risk aversion for the representative agent (see Yu and Yuan (2011)). Second, Hong and Sraer (2011) propose a model in which high market beta assets are endogenously more speculative due to their greater sensitivity to aggregate disagreement about the common cash flow factor. Extending their argument to general macro factors, one might conjecture that firms with high macro risk are more subject to the influence of market-wide sentiment (This conjecture is confirmed later in the data). Thus, high-risk firms are likely to be more overpriced than low-risk firms during high-sentiment periods. As a result, subsequent returns for high-risk firms could be lower than low-risk firms due to corrections to potential overpricing, despite higher systematic risk for high-risk firms.

Empirically, we find that all the beta-sorted portfolios have a positive return spread (0.61% per month on average) following low levels of sentiment (Hypothesis 1). We also find that the return spreads are significantly (1.17% per month) lower and negative (−0.56% per month) following high sentiment (Hypothesis 2). Moreover, we find evidence that high-risk portfolios earn lower returns following high investor sentiment, whereas low-risk portfolios have similar returns following low and high sentiment, supporting our conjecture that high-risk firms are more influenced by sentiment. In addition, further time-series regressions confirm a significant negative relation between investor sentiment and the return spreads between high- and low-risk portfolios. Finally, our results are robust to macroeconomic effects as well as the use of the survey-based Michigan consumer sentiment index.

Despite an insignificant average price of risk for economic factors, our results suggest that during periods when the market participants are more rational, pervasive factors are indeed priced. We regard this finding as supportive to standard theory. During high sentiment periods, however, sentiment-induced mispricing appears to dominate, thereby causing high-risk firms to earn lower subsequent returns. As we discuss in more detail later, time-variation in risk premium or in risk aversion under a rational framework could potentially contribute to the two-regime pattern, as long as this time-variation is correlated with our sentiment measure. Given the negative return spread between high- and low-risk firms during high-sentiment periods, however, our evidence suggests that sentiment-induced mispricing should at least play a partial role in the patterns we have documented since a fully rational model with time-variation in risk premium would have difficulty to produce a negative risk-return relation.

In terms of the literature, this study builds on the earlier work of Baker and Wurgler (2006, 2007), who argue that market-wide sentiment should have a greater effect on securities that are hard to arbitrage and difficult to value. Using observable proxies for these two characteristics, Baker and Wurgler (2006, 2007) demonstrate intriguing patterns in the cross section of returns across different sentiment states, which are consistent with the importance of those characteristics.

Our study is also related to Stambaugh, Yu, and Yuan (2011), which studies the effect of investor sentiment on anomalies. They find that anomalous return spreads are much more pronounced following **high sentiment** due to sentiment-induced overpricing. In a related setting, we examine the effect of investor sentiment on the pricing of macro risk factors, rather than on anomalies, and we argue that high-risk firms should earn higher returns than low-risk firms following **low sentiment** since macro-related factors should be correctly priced during such periods. Thus, our study focuses on the effect of sentiment on leading asset pricing models, whereas Stambaugh, Yu, and Yuan (2011) is silent in this aspect. Another related study is Yu and Yuan (2011), who show that there is a significant positive relation between the aggregate market's expected return and its conditional volatility during low-sentiment periods and a nearly flat relation during high-sentiment periods. We extend their investigation on the aggregate time-series risk-return tradeoff by exploring the much richer cross-sectional risk-return tradeoff for a large set of macro-related factors.[4]

Although our study shares a similar underlying setting with the above papers, our paper differs from earlier studies by focusing on the effect of sentiment on many leading asset pricing models simultaneously. Our findings also have distinctive implications for leading asset pricing models of cross-sectional returns. For example, the evidence that high-risk firms earn lower returns than low-risk firms during high sentiment poses a major challenge to traditional full-rational asset pricing models. On the other hand, the finding that high-risk firms earn higher returns than low-risk firms following low sentiment lends support to the traditional models during periods when market participants are closer to rational. Lastly, we view sharing a similar setting with existing studies as an advantage of our study, rather than a disadvantage. Using similar ingredients to account for a different set of asset pricing phenomena provides further validation on the

[4]Pioneered by French, Schwert, and Stambaugh (1987), there is also a vast literature exploring the traditional risk-return tradeoff under rational framework.

importance of the sentiment channel in asset price movements and suggests that the sentiment effect is pervasive, rather than an artifact of the data.[5]

Finally, this paper is also related to studies on the failure of the traditional CAPM model. Previous studies have suggested several forces responsible for the empirical failure of the CAPM, such as leverage aversion (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993), Baker, Bradley, and Wurger (2011)), money illusion (Cohen, Polk, and Vuolteenaho (2005)), and disagreement (Hong and Sraer (2011)). We show that the sentiment effect remains robust after controlling for these important economic forces.

The rest of the paper is organized as follows. In Section 2, we develop our hypotheses. Section 3 describes the investor sentiment data and discusses the underlying macro factors and the portfolios based on those factors. Section 4 reports the main empirical results. In Section 5, we investigate the robustness of our results and discuss alternative interpretations of our findings. Section 6 concludes.

1.2 Hypotheses Development

As discussed in the introduction, the prices of risk for most macro-related factors are insignificant on average. In this section, we develop hypotheses that explore sentiment-induced mispricing as at least a partial explanation for this empirical finding. As in Stambaugh, Yu, and Yuan (2011), our hypothesized setting combines two prominent concepts: market-wide sentiment and short-sale impediments. However, rather than focus on asset-pricing anomalies as in their study, we focus on the resulting implications

[5]Our approach is reminiscent of the studies on habit formation. Campbell and Cochrane (1999) show that external habit formation can help account for the equity premium puzzle, and in later studies Wachter (2006) and Verdelhan (2010) show that the exact same mechanism can account for bond return predictability and the forward premium puzzle, respectively. These subsequent studies thus further validate the role of habit formation on asset price dynamics.

on the pricing of macro risk factors.

Many studies argue that the beliefs of many stock market investors share a common time-varying sentiment component that exerts market-wide effects on stock prices. Early studies typically focus on the effect of market-wide sentiment on aggregate stock returns. The evidence on the sentiment effect is not particularly strong. More recent studies borrow insights from advances in behavioral finance theory and provide much sharper tests for the sentiment effect on the cross-section of stock returns. Baker and Wurgler (2006), for example, discover that after higher market-wide sentiment, firms that are more subject to the influence of sentiment experience lower subsequent returns, whereas after lower market-wide sentiment, firms that are hard to value and arbitrage earn higher subsequent returns than firms that are easy to value and arbitrage.

Similar in spirit to Stambaugh, Yu, and Yuan (2011), combining market-wide sentiment with Miller's (1977) insight that stock prices reflect an optimistic view due to the effect of short-sale impediments leads to the implication that the stock market is more rational and efficient during low-sentiment periods.[6] During periods of high market-wide sentiment, the most optimistic views about many stocks tend to be overly optimistic, so many stocks tend to be overpriced. During low-sentiment periods, however, the most optimistic views about many stocks tend to be those of the rational investors, and thus mispricing during those periods is less likely.

Recently, Hong and Sraer (2011) propose a theoretical model in which assets with high market beta are endogenously more speculative due to their greater sensitivity to aggregate disagreement about the common cash flow factor. Due to short-sale impediments, firms with high market beta are likely to be more overpriced when aggregate

[6]Numerous studies have argued that there exist short-sale impediments in the stock market. These impediments include, but not limited to, institutional constraints, arbitrage risk (Pontiff (1996), Shleifer and Vishny (1997), and Wurgler and Zhuravskaya (2002)), behavioral biases of traders (Barber and Odean (2008)), and trading costs (D'Avolio (2002)).

disagreement, and hence market-wide sentiment, is large, leading to the failure of the CAPM. Extending their argument to a multi-factor setting where the underlying factors are the macro-related variables, we further conjecture that firms with high macro risk are more subject to the influence of market-wide sentiment. Consider the market factor as an example. If the stock market return is affected by investor sentiment, then high-beta firms are automatically more influenced by sentiment. More important, we empirically confirm this conjecture in the data. Combining the insights from Stambaugh, Yu, and Yuan (2011) and Baker and Wurgler (2006) with the above conjecture, we can reach our three testable hypotheses.

First, during low-sentiment periods, the market tends to be more rational, since pessimistic investors stay out of the market due to short-sale impediments and marginal investors tend to be rational. Thus, firms with high macro risk should earn higher subsequent returns due to the classic risk-return tradeoff. Second, it is plausible that low-sentiment periods coincide with periods with higher market risk premia. Thus, it is easier to identify a significant return spread during low-sentiment periods. Third, if firms with high macro risk are more subject to the influence of sentiment, the returns of firms with high macro risk should be higher following low-sentiment periods than firms with low macro risk due to sentiment-induced underpricing (see, e.g., Baker and Wurgler (2006)). These effects reinforce each other, and hence the return spread between high- and low-risk firms should be positive during low-sentiment periods. However, if underpricing is less prevalent, the last effect might be very weak in reality.

We examine 10 pervasive macro-related variables. If each of these variables is truly a priced risk factor in an efficient market, we then reach our first hypothesis.

Hypothesis 1: The return spread between high- and low-risk portfolios should be positive following low investor sentiment.

On the other hand, during high-sentiment periods, there are two opposing effects.

First, as in the low-sentiment period, firms with high macro risk should earn higher returns due to the traditional risk-return tradeoff. However, this tradeoff is likely to be weaker during high-sentiment periods, since optimistic investors tend to demand lower compensation for bearing risk (see, e.g., Yu and Yuan (2011)).[7] Second, firms with high macro risk are likely to experience lower future returns, since these firms, which are typically more subject to the sentiment influence, are more overpriced than low-risk firms during high sentiment. Taken together, the return spread between high and low macro risk firms should be smaller during high-sentiment periods than during low-sentiment periods. In addition, the return spreads could even be negative if the second effect dominates. This is especially true if the macro factor is not strongly priced (a weak first effect) or if the high macro risk firms are much more subject to the influence of investor sentiment than the firms with low macro risk (a strong second effect). Thus, we arrive at our second hypothesis.

Hypothesis 2: The return spread between high- and low-risk portfolios should be smaller and potentially negative following high investor sentiment.

Finally, since high-risk firms are conjectured to be more subject to the influence of investor sentiment, high-risk firms should be relatively more overpriced and earn lower returns following high sentiment than following low sentiment. On the other hand, firms with low risk are less subject to the effect of investor sentiment, and hence low-risk firms should earn similar returns following high and low investor sentiment. In sum, we arrive at our third hypothesis, which is a direct implication from the conjecture based on Hong and Sraer (2011).

Hypothesis 3: High-risk portfolios should have lower returns following high investor sentiment than following low sentiment, whereas low-risk portfolios should have similar

[7] As we will discuss in more detail in Section 1.5.1, it is also conceivable that high-sentiment periods coincide with lower market risk premia. Thus, the return spread between high- and low-risk firms should be lower during high-sentiment periods.

returns following low and high sentiment.

One should not expect Hypothesis 3 to literally hold for all the beta-sorted portfolios. For example, if low-risk firms are also subject to, albeit to a lesser extent, the influence of investor sentiment, then high sentiment should forecast a lower subsequent return for low-risk firms as well.

It is worthwhile to emphasize that while our study shares a similar setting with Stambaugh et al. (2011), we focus on distinct implications. Stambaugh et al. (2011) examine the effect of sentiment on anomalies which should be more pronounced during *high-sentiment* periods, whereas our study focuses on risk factors, which should be more significantly priced during *low-sentiment* periods. Moreover, our analysis below can be viewed as an out-of-sample test of the same economic mechanism of combining short-sale impediments and market-wide sentiment. Showing supporting evidence in different applications makes us far more confident on the empirical relevance of this mechanism.

Finally, many fundamental mechanisms, including money illusion (Cohen, Polk, and Vuolteenaho (2005)) and the combination of divergence of opinions and short-sale constraints (Miller (1977) and Hong and Sraer (2011)), can potentially lead to mispricing in the stock market. In the current study, we simply use investor sentiment of Baker and Wurgler (2006) as a proxy for mispricing, and we do not model or investigate possible underlying forces which lead to mispricing in the first place. Instead, we focus on the effect of stock market mispricing on the pricing of macro-related factors.

1.3 Data Description: Investor Sentiment and Macro Factors

1.3.1 Investor Sentiment

For our main analysis, we use the market-based sentiment measure constructed by Baker and Wurgler (2006) (hereafter, the BW sentiment index). The monthly BW sentiment index spans from July 1965 to December 2010. Baker and Wurgler (2006) form their composite sentiment index based on six individual sentiment proxies: the number of initial public offerings (IPOs), the average first-day returns of IPOs, the dividend premium, the closed-end fund discount, the New York Stock Exchange (NYSE) turnover, and the equity share in new issues. To purge the effects of macroeconomic conditions from their sentiment index, Baker and Wurgler (2006) first regress each of the individual proxies on six macroeconomic indicators: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and a National Bureau of Economic Research (NBER) recession indicator. To further filter out idiosyncratic fluctuations in the six proxies and captures their common component, they take the first principal component of the six residual series from the regressions as their final composite index.

The BW sentiment index is plotted in Figure 1. It appears that the BW sentiment index lines up well with anecdotal accounts of fluctuations in sentiment, such as the so-called electronics bubble in 1968 and 1969, the biotech bubble in the early 1980s, and the internet bubble in the late 1990s. Finally, sentiment falls during the recent financial crisis and remains at a low level. Notice that sentiment is not extremely low during the recent financial crisis, which suggests that investors appear not to be excessively pessimistic during the financial crisis.

1.3.2 Macro-Related Factors

In addition to the macroeconomic variables originally studied by Chen, Roll, and Ross (1986), we explore a few new macro-related variables that are also likely to have pervasive effects on asset prices. These variables includes TFP growth, labor income growth, and aggregate market volatility. Below we briefly describe these macro-related factors.

In total, we consider 10 macroeconomic variables.

1: Consumption Growth

The seminal work of Lucas (1978) and Breeden (1979) shows that an asset should command a higher risk premium only if it covaries more with consumption growth. However, numerous studies find that the standard consumption-based CAPM tends to be rejected in cross-sectional tests. For example, Chen, Roll, and Ross (1986) find that consumption growth is not significantly priced by portfolios sorted by firm size. Following Chen, Roll, and Ross (1986), we choose monthly consumption growth (CON) as our consumption risk factor. Our results remain robust to quarterly consumption growth. The data on nondurables and services are obtained from the Bureau of Economic Analysis (BEA).

2 & 3: TFP Growth and Industrial Production Growth

Standard production-based asset-pricing models show that aggregate TFP growth should be positively priced. Firms with high exposure to aggregate TFP shocks should earn higher returns, since these firms perform badly during recessions (e.g., Jermann (1998), Gourio (2007), and Belo (2010)). We use both quarterly Solow residuals and monthly industrial production growth (IPG) as our measure of aggregate productivity shocks.[8]

4 & 5: Term Premium and Default Premium

[8]Following Chen, Roll, and Ross (1986), we lead industrial production and TFP by one period since industrial production at month t actually is the flow of industrial production during month t.

When investment opportunities vary over time, the multifactor models of Merton (1973) and Ross (1976) show that risk premia are associated with the conditional covariances between asset returns and innovations in state variables that describe the time variation of the investment opportunities. It has been shown that both the term premium (TERM) and the default premium (DEF) are countercyclical and have predictive power for the stock market and the bond market. Thus, it is conceivable that these variables are pervasive macro variables and that they describe the changing investment opportunities in the sense of Merton's (1973) ICAPM. Here, the term premium is measured as the difference between the 20-year Treasury bond yield and the 1-year Treasury bond yield. The default premium is calculated as the difference between the BAA corporate bond yield and the AAA bond yield. Instead of estimating innovations in the term and default premia, we simply define the factors as the first difference of the corresponding raw variables. This approach allows us to avoid potential look-ahead biases and econometric mis-specifications.

6 & 7: Unexpected Inflation and Changes in Expected Inflation

Inflation is another pervasive factor, considered by Chen, Roll, and Ross (1986). They consider both unanticipated inflation (UI) and changes in expected inflation (DEI). We follow their approach in constructing these two factors. Specifically, let $I_t \equiv \log(CPI_t) - \log(CPI_{t-1})$, where CPI_t is the consumer price index at time t. Then, the unexpected inflation is defined as $UI_t = I_t - E_{t-1}(I_t)$, and changes in expected inflation are measured as $DEI_t = E_t(I_{t+1}) - E_{t-1}(I_t)$. Notice that the resulting unanticipated inflation variable, UI_t, is perfectly negatively correlated with the unanticipated change in the real interest rate. Thus, we do not consider the real rate as a macro factor in our study. Finally, following Fama and Gibbons (1984), the expected inflation is estimated by modeling the changes in inflation as an MA(1) process.

8: Aggregate Market Volatility

A growing recent literature examines the pricing of aggregate volatility risk.[9] Since increasing volatility typically represents a deterioration in investment opportunities, Campbell (1993, 1996) and Chen (2002) argue that investors want to hedge against changes in market volatility. In addition, periods of high volatility also tend to coincide with downward market movements (see, e.g., French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992)). As a result, assets that have high sensitivities to innovations in market volatility are attractive to risk-averse investors. The higher demand for stocks with high volatility betas increases their price and lowers their average return. In sum, economic theory suggests a negative price of risk for innovations in market volatility. Following French, Schwert, and Stambaugh (1987), we calculate monthly market volatility from daily stock returns, and changes in monthly volatility are used as the volatility factor.

9: ***Market Returns***

Although the main focus of our study is to examine the relation between nonequity economic variables and stock returns, the market return is also a natural pervasive factor to consider given the prominence of CAPM (e.g., Sharpe (1964) and Lintner (1965)). Previous studies typically find that the market return is not significantly priced in the cross section of stock returns (see, e.g., Fama and French (1993)).[10] Many studies have suggested possible forces responsible for the empirical failure of the CAPM, such as leverage aversion (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993),

[9]Among others, see, Coval and Shumway (2001), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), Bansal, Kiku, Shaliastovich, and Yaron (2011), and Campbell, Giglio, Polk, and Turley (2011).

[10]Stambaugh et al. (2011) have also studied portfolios based on market beta from a different aspect. They, for example, do not emphasize our key hypothesis on the positive price of risk during low-sentiment periods, since the market is likely to be more efficient during those periods. More important, none of the other nine macro-related factors is examined by Stambaugh et al. (2011). In a contemporaneous paper, Antoniou, Doukas, and Subrahmanyam (2013) also investigate the role of sentiment in the failure of the CAPM, and their results are consistent with ours.

Baker, Bradley, and Wurger (2011)), money illusion (Cohen, Polk, and Vuolteenaho (2005)), and disagreement (Hong and Sraer (2011)). Here, we suggest another possible, but related, mechanism: the investor sentiment-induced overpricing.

10: Labor Income Growth

Following Fama and Schwert (1977), Campbell (1996) and Jagannathan and Wang (1996) argue that the human capital should be part of the market portfolio in the CAPM and labor income growth may proxy for the return on human capital. They find that labor income growth indeed has a significant and positive price of risk in cross-sectional tests of the CAPM. Subsequent studies, including Lettau and Ludvigson (2011) and Santos and Veronesi (2006), also use labor income growth (LAB) as a factor in cross-sectional tests. Following Jagannathan and Wang (1996), we construct monthly labor income growth as an additional macro factor.

Table 1 reports the summary statistics for these macro factors. In general, the correlations among these factors are quite low. The autocorrelations are also quite low, which validates these variables as legitimate candidates for risk factors.

1.3.3 Beta-Sorted Portfolios

In a seminal study, Chen, Roll, and Ross (1986) use size-sorted portfolios as testing portfolios to examine the pricing of macro risk factors. Two and a half decades later, there is now a large set of firm characteristics based on which large portfolio return spreads can be obtained. Thus, there are many potential sets of testing portfolios. It is, sometimes, hard to interpret the evidence on the pricing of macro risk factors based on one particular set of testing portfolios. For example, investment-specific shocks are positively priced using 10 momentum portfolios as testing portfolios (Li (2011)), but negatively priced using 10 book-to-market portfolios as testing portfolios (Papanikolaou

(2011)).[11]

Instead of relying on any specific firm characteristic to form testing portfolios, we utilize an alternative, yet complementary, approach in the literature. We construct portfolios by sorting individual stocks on their sensitivity to macro factors. This approach does not allow for the freedom in choosing testing portfolios and provides a natural way to produce spreads in exposure to risk factors for testing portfolios. Thus, these beta-sorted portfolios are particularly well suited for our study.

Before we form the beta-sorted portfolios, we briefly discuss the sign of the price of risk for macro-related factors. Economic theory strongly suggests that consumption growth, productivity shocks, labor income growth, and the market return factor should be positively priced in the cross section of stock returns, whereas aggregate volatility should have a negative price of risk. In addition, since both the term premium and the default premium tend to increase during recession (see Keim and Stambaugh (1986) and Fama and French (1989)), where the marginal utility tends to be high. We thus conjecture a negative sign for these two factors.[12] Finally, given that positive inflation innovation tends to occur during economic booms, we conjecture that the price of risk for inflation has a positive sign.[13]

For each of these macro factors in monthly (quarterly) frequency, at the beginning of each year we sort all firms from NYSE/AMES/NASDAQ (except the financial firms) into deciles based on their sensitivity to the underlying macro factor using the previous five-years (eight-years) of data. Here we follow Fama and French (1992) in choosing a

[11] There is a growing literature linking macroeconomic variables to asset-pricing anomalies. Lewellen, Nagel, and Shaken (2010) and Daniel and Titman (2012) provide an empirical assessment of this literature.

[12] Note that DEF and TERM predict both future returns and future volatility with the same positive sign. Thus, Merton's (1973) ICAPM is ambiguous about the sign of the price of risk for TERM and DEF (see, Maio and Santa-Clara (2012)).

[13] Indeed, the correlations of TERM and DEF to productivity and consumption shocks are all negative, while the correlations of UI and DEI to productivity and consumption shocks are all positive.

five-year formation window for monthly factors. We also skip one period to ensure that all the data is available at portfolio formation. The portfolios are held for one year. We then calculate the monthly value-weighted portfolio returns within each decile of portfolios. Our results are similar if the portfolios are rebalanced quarterly. We order the portfolio such that portfolio 10 is always the one with the highest macro risk, while portfolio 1 is the safest portfolio. We then construct a high-minus-low strategy using the extreme deciles, 1 and 10, with a long position in the high-risk decile and a short position in the low-risk decile.

In addition, we construct several combination/average portfolio strategies that take equal positions across individual portfolio strategies based on macro factors. The first combination strategy uses only portfolios based on consumption growth, TFP growth, industrial production growth, aggregate volatility, labor income growth, and market excess returns, since there is extremely strong economic intuition for the sign of the price of risk for these six factors. Because our prior on the sign of the price of risk for other factors is not as strong as the previous six variables, we gradually add the rest of factors into the combination portfolio strategies. As a result, our second combination strategy includes the term premium and the default premium in addition to the original six factors; the third combination strategy is the average across all 10 factors.

Table 2 reports summary statistics of monthly returns on the long-short strategies across all months in our sample period. Panel A indicates that the correlations among the high-minus-low portfolio returns are not particularly high. In addition, for the 10 individual high-minus-low portfolio returns, the percentages of overall variance explained by each of the first five principal components are $[0.40, 0.16, 0.09, 0.07, 0.06]$. Even the last principal component explains 3% of the variation. Given the low correlations between these underlying macro-related factors as shown in Table 1, it is not surprising that the correlations between return spreads are not particularly large.

Panel B of Table 2 shows that none of the 10 high-minus-low strategies produce significant positive average return spreads. The average return spread for the third combined strategy is an insignificant 3 basis points (bp) per month. In addition, many return spreads are actually negative. For example, the firms with high consumption risk earn a lower subsequent return than firms with low consumption risk. The biggest long-short return spread is based on industrial production growth, which is 39 bp per month and is statistically significant. Overall, the return spreads based on the sensitivity to underlying macro factors are typically insignificant, a result that is quite disappointing to leading economic models. These findings are not surprising. Existing evidence on the pricing of macro risk factor is relatively weak, probably due to measurement errors.

Panel C of Table 2 reports the ex post beta of the high-risk portfolio, the low-risk portfolio, and their difference. In general, the ex post beta spread is positive as expected. Many of the spreads are significant. Given the relatively low correlation between the stock market return and some of the macro factors, we view the positive ex post beta spread as reasonably big. More important, despite the marginally significant ex post beta spread, we still obtain a clear two-regime pattern in portfolio returns as we show below.

Frazzini and Pedersen (2011) show that leverage and margin constraints lead to the failure of CAPM and that assets with higher market beta earn lower risk-adjusted returns in various asset classes. Our results share a similar flavor: firms with higher beta with respect to various macro risk factors tend to have similar returns with the firms with lower beta. Thus, while Frazzini and Pedersen (2011) suggest betting against beta in various asset classes, our results suggest betting against various macro betas. In the next section, we go one step further by investigating the role of sentiment behind this result.

1.4 Main Empirical Analysis

Our empirical design is closely related to Stambaugh et al. (2011), by replacing their anomalies with our beta-sorted portfolios. Thus, the presentation of our empirical results closely follows their structure.

1.4.1 Average Returns across Two Sentiment Regimes

We first use the BW investor sentiment index to classify the entire period into high- and low-sentiment periods: a month is classified as high-sentiment (low-sentiment) if the sentiment level in the previous month is in the top (bottom) 50% of the entire sentiment series. We then compute average portfolio returns separately for these two regimes. Incidentally, out of the 84 months of NBER recession during our sample, 52 months are classified as high-sentiment, and only 32 months are classified as low-sentiment. Table 3 reports our main results.

Consider first Hypothesis 1, which predicts that the return spread between high- and low-risk portfolios should be positive following low sentiment. Table 3 reveals that each of the high-minus-low spreads exhibits positive average profits following low sentiment. At a 0.05 significance level, the (one-tailed) t-statistics for 6 of the 10 long-short portfolios reject the null hypothesis of no positive return spread following low sentiment. Here the one-tailed test is appropriate, since the alternative is a positive return spread. The average high-minus-low spread earns 61 bp per month following low sentiment, with a t-statistic equal to 3.00. This result is in sharp contrast to the insignificant overall return spreads in Table 2: the average spread between high- and low-risk firms is only 3 bp per month. Overall, the results in Table 3 provide strong support for Hypothesis 1. This evidence suggests that the traditional economic theory works well, as long as the market participants are close to being rational. Thus, despite potential measurement errors in beta estimation, the findings in Table 3 lend support to standard economic theory.

Next consider Hypothesis 2, which predicts that average return spreads between high- and low-risk portfolios should be significantly lower (and potentially negative) following high sentiment than following low sentiment. The support for this hypothesis is also strong. In Table 3, return spreads between high- and low-risk firms are positive following low sentiment, whereas these spreads are significantly lower and negative following high sentiment (see the last three columns). Indeed, all of the spreads are consistently positive following low sentiment and consistently negative following high sentiment. In the last column, nine of them have t-statistics that reject the no-difference null in favor of Hypothesis 2 at a 0.05 significance level. The last average return spread between high- and low-risk portfolios is 117 bp higher per month (with t-statistic -4.05) following low sentiment than following high sentiment. In addition, the last average return spread is -56 bp per month following high sentiment with t-statistics -2.88. Similar results hold for the first and the second average portfolios. Again, these findings are in sharp contrast to the near zero unconditional return spreads in Table 2.

As discussed in the introduction, one might argue that the measurement errors in betas could lead to a low average return spread between high- and low-risk firms. We certainly do not rule out the potential role of measurement errors in the observed insignificant *average return spread* between high- and low-risk firms. However, since measurement errors in betas tend to reduce the true beta spread between high- and low-risk portfolios, it is more difficult to identify a positive return spread between high- and low-risk firms following low sentiment. In addition, taking this measurement error view to the extreme that the measured betas are pure noise, we should observe near zero return spreads between high- and low-risk firms following both high and low sentiment. Thus, the noises in beta estimation are likely to *weaken* the two-regime pattern we have documented above.

Finally, consider Hypothesis 3, which predicts that sentiment should exert a stronger effect on high-risk portfolios and a weaker or no effect on low-risk portfolios. Table 3 shows that high-risk portfolios earn lower returns following high sentiment, and all 10 factors have a t-statistic that rejects the no-difference null in favor of Hypothesis 3. Low-risk portfolios also tend to earn lower returns following high sentiment, but the magnitude is very small and none of the 10 factors is significant. For example, low-risk portfolios in the combination strategy earn 49 bp per month lower following high sentiment, but the t-statistic is only -0.95. Any evidence for sentiment effects on low-risk portfolios become even weaker after benchmark adjustment (as discussed below in Table 4). Overall, the evidence appears to be consistent with Hypothesis 3 as well.

A standard approach in the existing literature is to use the Fama-French three-factor model to adjust for risk compensation. If the Fama-French three-factor model can capture all of the risk, then there should be no Fama-French three-factor benchmark-adjusted return spread between high- and low-risk portfolios, even following low-sentiment periods. However, it seems unlikely that the Fama-French three-factor model captures all of the pervasive macro risk. Table 4 reports results for benchmark-adjusted excess returns. After benchmark adjustment, 5 of the 10 individual t-statistics reject the null in favor of Hypothesis 1, and the combined high-minus-low risk portfolio spread still earns 39 bp per month following low sentiment (t-statistic: 2.62). This evidence suggests that the Fama-French three-factor model does not capture all of the macro risk.

Adjusting for benchmark exposure does not affect the main conclusion from Table 3. For example, the average return spread between high- and low-risk portfolios is 97 bp higher per month (with t-statistic -4.32) following low sentiment than following high sentiment. Moreover, the benchmark-adjusted return on the low-risk portfolios in the combined strategy exhibits an insignificant and positive 8 bp difference between high-and low-sentiment periods. In Table 4, none of the t-statistics reject the no-difference null in favor of higher returns following low sentiment. In fact, 6 of the 10 differences go in the opposite direction. On the other hand, the benchmark-adjusted return on the high-risk firms in the combined strategy exhibits a significant and negative 89 bp difference between high- and low-sentiment periods. Thus, after controlling for the Fama-French three factors, the evidence is still consistent with the view that investor sentiment induces more mispricing in high-risk firms and induces little, if any, mispricing in low-risk firms.

It is worth noting that most of the low-risk portfolios earn close to zero benchmark-adjusted return following both high- and low-sentiment periods, suggesting that Fama-French three factors explain the cross-section of expected return among low-risk firms, which are not very sensitive the sentiment influence. However, all 10 high-risk portfolios earn negative benchmark-adjusted returns following high sentiment. The average benchmark-adjusted returns are significant negative (-0.57% per month with t-statistic 3.65), again suggesting overpricing for high-risk firms during high-sentiment periods. In contrast, 9 out of 10 high-risk portfolios earn positive benchmark-adjusted returns following low sentiment. The average benchmark-adjusted returns are also significant and positive (0.33% per month with t-statistic 2.20), suggesting either that Fama-French three factors do not capture all the macro risk among high-risk firms, or underpricing for high-risk firms during low-sentiment periods.

Finally, one might argue that our two-regime results could be mechanical. If a variable (e.g., sentiment) can predict market excess returns, then automatically, the market price of risk for the market factor is lower following high sentiment than low sentiment. This is also consistent with the notation that sentiment captures time-variation in risk premia. However, the market excess return is still 0.25% per month following high sentiment. Thus, the market risk premium is still positive following high sentiment, albeit lower than that following low sentiment, which is 0.61% per month. Thus, our negative market price of risk following high sentiment is not a mechanical result. In the robustness checks section, we discuss the possibility that sentiment is a proxy for time-variation in risk aversion or risk premia in more detail.

Overall, the evidence in Tables 3 and 4 appears to support the traditional theory during low sentiment and suggests that market-wide sentiment creates overpricing, probably due to short-sale impediments, which in turn destroy the traditional risk-return tradeoff during high sentiment.

1.4.2 Predictive Regressions

In the previous subsection, we report the average portfolio returns within two sentiment regimes, where the regime classification is simply a dummy variable. In this subsection, we conduct an alternative analysis, using predictive regressions to investigate whether the level of the BW sentiment index predicts returns in ways that are consistent with our hypotheses. The regression approach allows us to easily control for other popular risk factors (e.g., the Fama-French three factors) and macro variables, which enables us to check that the sentiment effect we documented in the previous subsection is not just due to comovement with common factors. Table 5 reports the results of regressing excess returns on the lagged sentiment index.

Taken together, Hypotheses 1 and 2 predict a negative relation between the profitability of each high-minus-low risk portfolio spread and investor sentiment. Consistent with this prediction, the slope coefficients for the spreads based on all 10 factors are positive in Table 5. Eight of the individual t-statistics are significant at a one-tailed 0.05 significance level. The last combination strategy has a t-statistic of -4.26 in Table 5. Here, returns are measured in percentage per month, and the sentiment index is scaled to have a zero mean and unit standard deviation. Thus, for example, the slope coefficient of -0.55 for the combination strategy indicates that a one-standard-deviation increase in sentiment is associated with a 0.55% decrease per month in the long-short portfolio strategy.

Hypothesis 3 predicts a negative relation between the returns on the high-risk portfolio and the lagged sentiment level. Consistent with this prediction, the slope coefficients for the high-risk portfolios based on all 10 factors are negative. Moreover, all 10 individual t-statistics are highly significant. The last combination strategy has a t-statistic of -3.15. We see that a one-standard-deviation increase in sentiment is associated with a 1.07% lower monthly excess return on the high-risk portfolio. Hypothesis 3 also predicts a weaker relation between the returns on the low-risk portfolio and the lagged sentiment level. Consistent with this prediction, the slope coefficients for the low-risk portfolios based on all 10 factors are smaller in magnitude. For example, the last average strategy in Table 5 has a slope of -0.51, which is less than half of the magnitude for the average high-risk portfolio but is nevertheless significant.

Table 6 reports the results of regressing benchmark-adjusted returns on the lagged sentiment index. Incidentally, we find that after benchmark adjustment, there is no significant relation between returns on the low-risk portfolios and lagged sentiment. Here, we see that benchmark adjustment makes a noticeable difference. Without benchmark adjustment, the coefficients for the low-risk portfolio returns are all negative, and 6 of the 10 are significant at a 0.05 significance level for a one-tailed test (see Table 5). After adjusting for benchmark exposures, however, the results are largely in line with Hypothesis 3. In Table 6, 5 of the 10 low-risk portfolio slopes are insignificantly positive, and none of the five negative slopes is significant either. The average strategy has a tiny slope of -0.02 and a t-statistic of -0.26, thus confirming our conjecture that low-risk firms are much less sensitive to the influence of investor sentiment. On the other hand, the high-risk firms are still highly influenced by sentiment even after benchmark adjustment. Finally, the benchmark-adjusted return for the high-minus-low risk portfolio is harder to interpret based on our hypothesis due to the mixture of risk and mispricing. Nonetheless, for completeness we report the results for benchmark-adjusted long-short portfolios in the last two columns of Table 6.

Finally, we regress beta-sorted portfolio returns on contemporaneous sentiment changes. If the conjecture that high-risk firms are more subject to the influence of sentiment is true, we should observe a stronger comovement between returns on high-risk firms and sentiment changes. Indeed, Table 7 shows that the regression coefficient is larger for high-risk portfolios than for low-risk portfolios. This is true for all macro factors except DEI, for which the two-regime pattern is indeed slightly less evident (see Table 5 and 6).[14] Given this evidence, one might think that the higher return for high-risk firms might be due to the underpricing of these firms following low sentiment (e.g. Baker and Wurgler (2006)). However, we show in the next subsection that the underpricing effect seems to be much weaker than the overpricing effect. Thus, it is unlikely that sentiment-induced underpricing can account for all the positive return spread between high- and low-risk portfolios following low sentiment. Systematic risk seems a more plausible explanation for the positive return spreads during low-sentiment periods.

In sum, the predictive regressions in this subsection confirm the results from the simple comparisons of returns during high- and low-sentiment periods in the last subsection. Our evidence supports the view that sentiment-induced overpricing at least partially explains the insignificant average price of risk for the macro-related factors.[15]

[14]Interestingly, among all the beta-sorted portfolios, the low market beta portfolio has the lowest and close to zero exposure to sentiment, whereas the high market beta portfolio has the highest exposure to sentiment. This is probably due to the fact that market return itself is highly subject to the movement of sentiment, whereas other macro factors are less correlated with sentiment.

[15]Due to the small correlation between the predictive-regression residuals and the innovations in sentiment, the potential small-sample bias in predictive regressions, as studied by Stambaugh (1999), appears not to be a problem in the results reported here.

1.4.3 Sentiment Change as a Factor: Implications on Asymmetric Mispricing

Although traditional economic theory allows no role for investor sentiment, Delong et al. (1990) and other subsequent studies argue that changes in sentiment itself present risk to arbitrageurs.[16] Thus, one might be interested in using sentiment itself as a risk factor. We repeat our analysis using sentiment as a factor. We find that firms with high exposure to sentiment changes earn higher returns following low sentiment, whereas the opposite is true following high sentiment. These findings are consistent with Baker and Wurgler (2006), who argue that firms that are more subject to the influence of sentiment (i.e., firms with high exposure to sentiment changes) should be more overpriced (underpriced) following high (low) sentiment. Baker and Wurgler (2006) use a few firm characteristics as proxies for the degree of sentiment influence. Instead of sorting on firm characteristics as in Baker and Wurgler (2006), however, one can form portfolios based directly on the sensitivity of firm returns to changes in sentiment. We take this complementary approach in Table 8.

In particular, the positive return spread following low-sentiment periods is consistent with both the concept of sentiment risk and the differential effect of the sentiment-induced mispricing across firms with different limits to arbitrage. In this study, we do not intend to distinguish these two alternative interpretations, since they might both be at play simultaneously. More important, the absolute magnitude of the spread following low sentiment is much lower than that following high sentiment (0.35% versus 1.21% per month). Moreover, part of the 35 bp could be due to the sentiment risk in the sense of Delong et al. (1990). Thus, the evidence seems to suggest that sentiment-induced overpricing is much more prevalent than sentiment-induced underpricing.

[16] Lee et al. (1991), for example, argue that noise traders' correlated trades create risk in the closed-end fund price above and beyond the riskiness of the underlying assets it holds. As a result, rational investors demand a risk premium for holding the fund, leading to closed-end fund discounts.

In addition, we repeat the regression analysis in Table 7 with sentiment-beta-sorted portfolios. As expected, the portfolio with low sentiment sensitivity has an insignificant regression coefficient of 0.33, while the portfolio with high sentiment sensitivity has a highly significant coefficient of 4.42. Thus, the high-minus-low portfolio has a coefficient of 4.08. With such a large exposure to sentiment, the high-minus-low portfolio based on sentiment changes has only a return spread of 0.35% per month following low sentiment. In contrast, Table 7 shows that although the average high-minus-low portfolio has a sentiment sensitivity coefficient of 1.17 (only about 1/4 of 4.08), the average return spread is 0.61% per month following low sentiment. Taken together, risk appears to be responsible for a large part of the observed positive return spread between high- and low-risk portfolios following low sentiment.

Another way to further confirm that sentiment-induced overpricing is more prevalent than underpricing is to use both the positive part and the negative part of sentiment to predict aggregate market returns. Panel C of Table 8 shows that the positive part of sentiment is a strong contrarian predictor for future aggregate market returns, whereas the negative part does not forecast market returns at all. In addition, the opposite sign obtains for the negative part. Thus, sentiment has predictive power only during high-sentiment periods, suggesting that sentiment-induced overpricing is more prevalent than sentiment-induced underpricing.

1.5 Robustness Checks

1.5.1 Interpretation Based on Time-Varying Risk Premia

One might argue that our findings could potentially be consistent with a risk-based explanation without resorting to irrational investor sentiment. In particular, if a higher risk premium on these risk factors or higher risk aversion coincides with periods with lower sentiment, part of our results could potentially obtain. For example, the high-minus-low return spread should be more positive following low sentiment. Many previous studies have documented that the market risk premium is countercyclical, and that variations in risk premia are typically correlated with business conditions (see, e.g., Keim and Stambaugh (1986) and Fama and French (1989)). Thus, it is worthwhile to repeat our previous analysis by controlling for business conditions.

In constructing their sentiment index, Baker and Wurgler (2006) have removed macro-related fluctuations by regressing raw sentiment measures on six macroeconomic variables: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and an indicator for NBER recessions. We control for an additional set of five macro-related variables that have been shown to be correlated with risk premia and business conditions: the default premium, the term premium, the real interest rate, the inflation rate, and Lettau and Ludvigson's (2001) wealth-consumption ratio (CAY). This set of macro variables is also used as control in Stambaugh et al. (2011).

By regressing excess returns on the lagged sentiment index and the five lagged macro-related variables, we investigate whether the predictive ability of sentiment for subsequent returns is robust to including macro-related fluctuations in addition to those already controlled for by Baker and Wurgler (2006). The regression results, reported in Table 9, indicate that the effects of investor sentiment remain largely unchanged by including the additional five variables. In particular, the coefficients and their t-statistics are close to those in Table 5, in which the five additional macro-related variables are not included in the regressions.[17]

[17]In untabulated results, we find that after benchmark adjustment, the returns on low-risk portfolios are not associated with lagged sentiment (coefficient = -0.02 and t-statistic = -0.35), whereas the returns on high-risk portfolios are significantly negatively associated with lagged sentiment (coefficient = -0.37 and t-statistic = -3.23), just as in Table 6.

Overall, if time variation in the risk premium drives our results, it appears that this variation is not strongly related to either the six macro variables controlled by Baker and Wurgler (2006) or the five additional variables included in our analysis. Of course, it could still be possible that the sentiment index itself captures time variation in risk, or risk aversion, which is not captured by the 11 macro variables. At the least level, we show that sentiment contains information regarding time variation in risk premia which is not captured by standard macro-related variables. More important, Yu and Yuan (2011) show that low-sentiment periods could be endogenously associated with periods of high effective risk aversion due to the limited market participation resulting from short-sale constraints or a convex demand function for stocks. Thus, it is theoretically feasible that sentiment can be related to effective risk aversion and hence the price of risk. In this broad sense, our sentiment-based interpretation is consistent with the time-varying risk aversion story.

Finally, as argued by Stambaugh, Yu, and Yuan (2012), investor sentiment could be related to macroeconomic conditions. It is quite possible that after favorable (adverse) macroeconomic shocks, some investors become too optimistic (pessimistic) and push stock prices above (below) levels justified by fundamental values. Thus, as long as high (low) sentiment makes overpricing (underpricing) more likely, the extent to which sentiment relates to the macroeconomy or risk aversion does not affect the implications explored in this study. For instance, even if there is a strong link between sentiment and risk aversion, there still remains the challenge of explaining, across all 10 macro-related factors, why high-risk firms earn lower returns following high sentiment. It appears that sentiment-induced mispricing, especially overpricing, is at least partially responsible for this empirical fact.

1.5.2 Alternative Sentiment Index

We also investigate the robustness of our results to using an alternative sentiment index: the University of Michigan Consumer Sentiment Index. Many previous studies regarding investor sentiment have used this index (e.g., Ludvigson (2004), Lemmon and Portniaguina (2006), and Bergman and Roychowdhury (2008)). While the BW sentiment index is a measure of sentiment based on stock market indicators, the Michigan sentiment index is a survey-based measure. The monthly survey is mailed to 500 random households and asks their views about both the current and expected business conditions. As a result, the Michigan sentiment index might be less tied to the sentiment of stock market participants. To remove the business cycle component from the index, we use the residuals from a regression of the Michigan index on the six macro variables used by Baker and Wurgler (2006).

Table 10 reports the results of regressing excess returns on the lagged Michigan sentiment index as well as on the lagged macro-related variables. Our three hypotheses are supported, with the Michigan index as a proxy for sentiment. For the average high-minus-low risk portfolio based on the 10 factors, the return spread is significantly lower following high sentiment than following low sentiment, and low-risk firms are not significantly affected by market-wide sentiment. The patterns of the results across the 10 macro factors are also similar to those obtained using the BW index, as reported in Table 5, although some of the patterns are slightly weaker. The weaker results would also be expected if the BW index is a better measure of the mood of stock market participants.[18]

[18] In untabulated analysis, we find that our results in Table 10 become slightly stronger when we use Conference Board Consumer Confidence Index as a proxy for investor sentiment. In addition, if we replace the total Michigan sentiment index with its expected business condition component, the patterns in Table 10 also become slightly stronger. These results, omitted for brevity, are available upon request.

1.5.3 Spurious Regression Critique

Because investor sentiment indices are quite persistent, our predictive regressions are subject to the spurious regression critique of Ferson, Sarkissian, and Simin (2003). To address this concern, we perform a simple Monte Carlo simulation analysis.

We independently simulate autoregressive artificial sentiment processes with the same persistence as the BW sentiment index. We then perform the same two-regime sentiment analysis as in Table 3 by using the simulated sentiment index. The corresponding t-statistics for the last column of Table 3 are collected. We repeat the above procedure for 1,000 times to obtain 1,000 by 13 t-statistics panel for the last column of Table 3. Panel A of Table 11 reports the 2.5%, 5%, 50%, 95%, and 97.5% quantiles of the t-statistics. It can be seen that the 2.5% quantiles are around -1.96. Thus, the spurious regression critique does not pose an issue for our analysis. We also perform the same analysis by using artificial sentiment index as a continuous variable as in Table 5. These results, omitted for brevity and available upon request, remain similar.

Panel B of Table 11 reports the fraction of simulations with all 10 t-statistics for individual macro-related factor less than a certain value. In general, it is very rare to obtain the same sign in those 10 individual regressions. For the two-regime analysis, there are only 2.8% chances that all the 10 beta-sorted portfolio has a higher spread following low sentiment than high sentiment. Using sentiment as a continuous variable yield essentially the same results. For example, none of these 1,000 simulation produce t-statistics simultaneously less than -1 for all 10 factors.

In sum, the spurious regression critique does not pose a problem for our results. Furthermore, it is quite rare to obtain a consistent sign for all the 10 macro-related factors in the analysis performed in both Table 3 and 5.

1.5.4 Controlling for Alternative Mechanisms

As mentioned earlier, many studies have suggested possible forces responsible for the empirical failure of the CAPM, such as leverage aversion, money illusion, and disagreement. Although we consider a much broader set of factors, it is still conceivable that the mechanisms proposed by these studies also work for our broad set of macro-related factors. Moreover, it is certainly possible that the forces proposed by these studies overlaps with our sentiment-channel. For example, when aggregate disagreement is high, there might be more overpricing due to short-sale impediments. Indeed, the correlation between sentiment and aggregate disagreement is about 54%. Thus, it is interesting to investigate whether sentiment still has predictive power after controlling for these mechanisms.

To investigate this possibility, in the Table 12, we perform the regression analysis by controlling for the effect from funding constraints (TED) of Frazzini and Pedersen (2011), the money illusion effect (inflation) of Cohen, Polk, and Vuolteenaho (2005) and aggregate dispersion of Hong and Sraer (2011) and Yu (2011). As shown in Table 12, the significant predictive power of sentiment for the high-minus-low return spreads remains quantitatively similar. Thus, our mispricing channel provides incremental predictive power for the high-minus-low risk portfolio returns.

In addition, in untabulated analysis, we study several additional factors proposed by recent studies. These factors include the cash flow news and the discount rate news of Campbell and Vuolteenaho (2004) and the average correlation and the average volatility factors of Chen and Petkova (2012). Similar to the 10 factors studied in the paper, we find that for these additional factors, the average return spreads between high- and low-risk firms are insignificant and close to zero. In addition, these spreads are positive following low sentiment periods, and negative following high sentiment periods.

The differences-in-differences are economically large and statistically significant. These results are available upon request.

Finally, notice that the BW sentiment index has a look-ahead bias due to the principal component analysis and orthogonalization, although the macro-related factors are observable in real time, Thus, in untabulated analysis, we form the sentiment index recursively in real time without the look-ahead bias, and we then repeat the analysis in Tables 3 and 8 with this new real-time sentiment index. These results, omitted for brevity and available upon request, remain quantitatively similar.

1.6 Conclusions

It is important to understand why firms with high exposure to macro risk factors do not earn higher unconditional expected returns. In this paper, we explore the possibility that sentiment-induced mispricing, especially overpricing, could at least partially explain the insignificant price of risk in pervasive macro-related risk factors. The evidence that high-risk firms earn significantly higher returns than low-risk firms during low-sentiment periods suggests that our economic theory is partly supported by the data, especially during the periods when market participants are more rational. However, given that the opposite is true following high-sentiment periods, it appears that mispricing also plays a role, and that it is important to incorporate investor sentiment into economic theory in future work.

Our hypotheses are direct implications of the combination of short-sale impediments and time-varying market-wide sentiment, which has been explored by several previous studies. Hence, the findings in this paper suggest that the *same* mechanism is working out of sample. Our reconfirming evidence greatly enhances our confidence that the impact of sentiment in asset prices documented in this paper and in previous studies (e.g., Baker and Wurgler (2006, 2007) and Stambaugh et al. (2011)) is not an artifact of the data, but is systematic and important.

Table 1.1: Correlations among the Macro Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				A. Correlations among macro factors						
(1) CON	1.00									
(2) TFP	0.42	1.00								
(3) IPG	0.52	0.32	1.00							
(4) $TERM$	-0.27	-0.17	-0.20	1.00						
(5) DEF	-0.16	-0.28	-0.28	0.19	1.00					
(6) UI	0.07	0.15	0.16	-0.09	-0.27	1.00				
(7) DEI	0.22	0.17	0.18	-0.11	-0.15	0.65	1.00			
(8) VOL	-0.03	-0.03	0.05	0.00	0.03	0.03	0.11	1.00		
(9) MKT	0.18	0.14	0.03	0.03	-0.05	-0.07	-0.14	-0.23	1.00	
(10) LAB	0.36	0.16	0.16	-0.13	0.00	0.03	0.07	-0.00	0.06	1.00
				B. Correlation between macro factors and B-W sentiment (%)						
S_{t-1}	-3.96	-9.68	-11.88	5.17	3.17	-6.13	-6.69	2.80	-7.02	-9.89
ΔS	22.05	17.30	4.58	-3.95	-9.22	16.04	11.23	-9.76	25.48	9.34
				C. Autocorrelation among the macro factors						
	1	2	3	4	5	6	7	8		
CON	-0.132	0.097	0.211	-0.013	0.062	0.046	0.046	0.088		
TFP	0.074	0.162	-0.071	-0.027	-0.119	-0.098	-0.066	-0.096		
IPG	0.354	0.294	0.288	0.234	0.110	0.116	0.069	0.089		
$TERM$	0.116	-0.021	-0.026	-0.076	-0.072	-0.079	-0.105	0.113		
DEF	0.285	-0.075	-0.073	0.030	0.135	-0.026	-0.188	-0.095		
UI	0.233	-0.048	-0.112	-0.082	-0.096	-0.034	-0.038	-0.043		
DEI	-0.023	-0.082	-0.016	-0.127	-0.129	0.045	-0.101	0.070		
VOL	-0.407	0.006	-0.030	-0.047	0.021	-0.024	0.020	-0.043		
MKT	0.091	-0.036	0.023	0.014	0.056	-0.054	-0.003	-0.041		
LAB	0.060	0.194	0.101	0.210	0.179	0.129	0.138	0.209		
$Sent.$	0.984	0.966	0.947	0.926	0.902	0.876	0.849	0.817		

The table reports the correlations among macro factors, the correlations between the BW sentiment index and macro factors, and the autocorrelations of degree 1 to 8 of macro factors. TFP growth is sampled at a quarterly frequency, and the rest of variables are sampled at a monthly frequency. To calculate the correlations between factors, monthly factors are time-aggregated to quarterly frequency. Both levels and changes in sentiment are taken directly from Baker and Wurger's online dataset. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.2: Macro-Factor-Based Portfolio Returns across All Months

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
		A. Correlations: High-minus-Low Risk Portfolios												
(1)	CON	1.00												
(2)	TFP	0.34	1.00											
(3)	IPG	0.36	0.14	1.00										
(4)	$TERM$	0.06	-0.02	0.23	1.00									
(5)	DEF	0.23	0.30	0.38	0.16	1.00								
(6)	UI	-0.10	-0.03	0.23	0.28	0.16	1.00							
(7)	DEI	-0.12	-0.04	0.20	0.21	0.21	0.55	1.00						
(8)	VOL	0.43	0.28	0.35	0.07	0.36	0.15	-0.04	1.00					
(9)	MKT	0.46	0.36	0.37	0.22	0.32	0.16	-0.02	0.66	1.00				
(10)	LAB	0.23	0.25	0.43	0.22	0.40	0.42	0.34	0.48	0.44	1.00			
(11)	$Ave1$	0.67	0.55	0.61	0.19	0.47	0.21	0.07	0.79	0.84	0.68	1.00		
(12)	$Ave2$	0.62	0.52	0.62	0.37	0.61	0.25	0.13	0.75	0.81	0.69	0.97	1.00	
(13)	$Ave3$	0.52	0.46	0.63	0.41	0.61	0.47	0.36	0.69	0.75	0.74	0.92	0.96	1.00

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
B. Excess Returns													
Means													
High Risk	0.29	0.75	0.79	0.52	0.40	0.52	0.46	0.49	0.45	0.16	0.49	0.48	0.48
Low Risk	0.46	0.38	0.41	0.32	0.54	0.52	0.52	0.35	0.49	0.60	0.45	0.44	0.46
High − Low	-0.17	0.36	0.39	0.20	-0.14	0.00	-0.06	0.15	-0.04	-0.44	0.04	0.04	0.03
t-statistics													
High Risk	0.77	2.10	2.06	1.49	1.07	1.58	1.39	1.20	1.00	0.39	1.28	1.30	1.36
Low Risk	1.53	1.36	1.27	0.97	1.95	1.60	1.52	1.46	2.80	2.03	1.87	1.78	1.75
High − Low	-0.70	1.49	1.86	0.79	-0.53	0.00	-0.24	0.54	-0.10	-1.53	0.22	0.23	0.16
C. Ex Post Betas													
Point Estimates													
High Risk	3.91	4.59	0.59	4.55	-2.88	-0.87	-6.78	-1.36	1.77	1.13			
Low Risk	2.30	3.06	0.37	-5.20	-6.56	-2.55	-7.71	-2.90	0.61	0.32			
High − Low	1.61	1.52	0.22	9.75	3.68	1.68	0.93	1.54	1.17	0.81			
t-statistics													
High Risk	4.48	3.43	1.23	0.46	-1.06	-0.45	-1.32	-3.49	25.27	1.52			
Low Risk	4.16	2.77	0.84	-0.43	-1.63	-1.32	-1.42	-5.59	13.42	0.59			
High − Low	2.32	1.85	0.96	1.42	1.68	1.83	0.43	4.99	10.89	1.90			

The table reports the correlation, the mean value, and t-statistics of beta-sorted portfolio returns across all months. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.3: Macro-Factor-Based Portfolio Returns during High and Low Sentiment

	Low Risk			High Risk			High − Low		
	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low
CON	0.19	0.73	-0.54	-0.48	1.06	-1.54	-0.67	0.33	-1.00
	(0.39)	(2.15)	(-0.92)	(-0.85)	(2.26)	(-2.08)	(-1.77)	(1.12)	(-2.06)
TFP	0.21	0.56	-0.35	0.08	1.42	-1.34	-0.13	0.86	-0.99
	(0.46)	(1.67)	(-0.64)	(0.14)	(3.26)	(-1.88)	(-0.35)	(2.68)	(-1.97)
IPG	-0.08	0.89	-0.97	-0.11	1.70	-1.81	-0.03	0.80	-0.83
	(-0.16)	(2.18)	(-1.48)	(-0.18)	(3.87)	(-2.38)	(-0.09)	(2.99)	(-2.12)
$TERM$	0.10	0.54	-0.44	-0.23	1.26	-1.49	-0.33	0.72	-1.05
	(0.19)	(1.36)	(-0.68)	(-0.43)	(2.86)	(-2.12)	(-1.00)	(1.99)	(-2.17)
DEF	0.46	0.62	-0.16	-0.50	1.30	-1.81	-0.96	0.69	-1.64
	(1.08)	(1.78)	(-0.30)	(-0.91)	(2.66)	(-2.39)	(-2.91)	(1.89)	(-3.35)
UI	0.22	0.82	-0.60	-0.22	1.27	-1.49	-0.45	0.45	-0.89
	(0.45)	(1.88)	(-0.90)	(-0.45)	(2.99)	(-2.29)	(-1.36)	(1.47)	(-2.00)
DEI	0.09	0.94	-0.85	-0.35	1.27	-1.62	-0.45	0.33	-0.78
	(0.18)	(2.29)	(-1.23)	(-0.70)	(3.01)	(-2.44)	(-1.22)	(1.05)	(-1.61)
VOL	0.09	0.61	-0.51	-0.32	1.31	-1.63	-0.41	0.70	-1.11
	(0.23)	(2.36)	(-1.09)	(-0.52)	(2.51)	(-2.01)	(-1.13)	(1.84)	(-2.09)
MKT	0.57	0.41	0.16	-0.45	1.35	-1.80	-1.02	0.94	-1.96
	(2.31)	(1.76)	(0.50)	(-0.67)	(2.32)	(-2.02)	(-1.74)	(1.92)	(-2.56)
LAB	0.26	0.94	-0.68	-0.92	1.24	-2.15	-1.17	0.30	-1.47
	(0.58)	(2.55)	(-1.18)	(-1.46)	(2.55)	(-2.69)	(-2.83)	(0.83)	(-2.67)
$Ave1$	0.21	0.69	-0.48	-0.37	1.35	-1.71	-0.57	0.66	-1.23
	(0.55)	(2.36)	(-1.02)	(-0.63)	(2.91)	(-2.27)	(-2.10)	(2.76)	(-3.31)
$Ave2$	0.22	0.66	-0.44	-0.37	1.33	-1.70	-0.59	0.67	-1.26
	(0.57)	(2.20)	(-0.89)	(-0.65)	(2.93)	(-2.31)	(-2.60)	(3.06)	(-3.87)
$Ave3$	0.21	0.71	-0.49	-0.35	1.32	-1.67	-0.56	0.61	-1.17
	(0.52)	(2.21)	(-0.95)	(-0.65)	(2.98)	(-2.35)	(-2.88)	(3.00)	(-4.05)

The table reports average portfolio returns in excess of the one-month T-bill rate in months following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all macro-factor-based portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.4: Benchmark-Adjusted Portfolio Returns during High and Low Sentiment

	Low Risk			High Risk			High − Low		
	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low
CON	-0.01	-0.03	0.02	-0.73	-0.02	-0.71	-0.72	0.01	-0.73
	(-0.04)	(-0.16)	(0.05)	(-3.98)	(-0.09)	(-2.61)	(-1.99)	(0.03)	(-1.59)
TFP	0.08	-0.10	0.18	-0.14	0.46	-0.60	-0.22	0.57	-0.78
	(0.36)	(-0.61)	(0.65)	(-0.59)	(2.02)	(-1.85)	(-0.62)	(1.78)	(-1.63)
IPG	-0.23	0.06	-0.29	-0.31	0.72	-1.03	-0.08	0.66	-0.74
	(-1.08)	(0.37)	(-1.08)	(-1.21)	(2.77)	(-2.91)	(-0.29)	(2.40)	(-1.94)
$TERM$	-0.13	-0.37	0.23	-0.36	0.44	-0.80	-0.23	0.81	-1.04
	(-0.56)	(-1.72)	(0.74)	(-1.58)	(2.11)	(-2.55)	(-0.70)	(2.44)	(-2.24)
DEF	0.33	-0.10	0.43	-0.79	0.21	-1.00	-1.13	0.31	-1.43
	(1.68)	(-0.66)	(1.78)	(-3.64)	(0.95)	(-3.13)	(-3.37)	(1.03)	(-3.21)
UI	-0.02	-0.12	0.10	-0.45	0.36	-0.81	-0.43	0.48	-0.91
	(-0.09)	(-0.73)	(0.40)	(-2.12)	(1.90)	(-2.76)	(-1.31)	(1.73)	(-2.09)
DEI	-0.08	0.01	-0.09	-0.56	0.47	-1.03	-0.48	0.46	-0.94
	(-0.39)	(0.05)	(-0.35)	(-1.93)	(2.60)	(-2.96)	(-1.37)	(1.77)	(-2.10)
VOL	-0.02	0.08	-0.10	-0.56	0.13	-0.69	-0.54	0.05	-0.59
	(-0.08)	(0.56)	(-0.40)	(-2.15)	(0.71)	(-2.14)	(-1.86)	(0.21)	(-1.56)
MKT	0.27	-0.08	0.35	-0.67	0.20	-0.86	-0.94	0.28	-1.22
	(1.52)	(-0.60)	(1.64)	(-2.95)	(0.85)	(-2.72)	(-2.87)	(0.90)	(-2.82)
LAB	-0.02	0.05	-0.07	-1.10	0.30	-1.40	-1.09	0.25	-1.33
	(-0.09)	(0.30)	(-0.29)	(-3.77)	(1.28)	(-3.63)	(-3.13)	(0.77)	(-2.74)
$Ave1$	0.01	-0.00	0.02	-0.58	0.30	-0.88	-0.60	0.30	-0.90
	(0.11)	(-0.05)	(0.12)	(-3.25)	(1.79)	(-3.56)	(-3.30)	(1.76)	(-3.44)
$Ave2$	0.03	-0.06	0.10	-0.58	0.31	-0.89	-0.62	0.37	-0.98
	(0.28)	(-0.78)	(0.67)	(-3.74)	(1.99)	(-3.91)	(-4.07)	(2.42)	(-4.27)
$Ave3$	0.02	-0.06	0.08	-0.57	0.33	-0.89	-0.58	0.39	-0.97
	(0.15)	(-0.73)	(0.55)	(-3.65)	(2.20)	(-3.99)	(-3.95)	(2.62)	(-4.32)

The table reports average benchmark-adjusted portfolio returns following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. The average returns in high- and low-sentiment periods are estimates of a_H and a_L in the regression, $R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t}$, where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-sentiment periods, and $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.5: Predictive Regressions for Excess Returns on Long-Short Strategies

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.55	-1.98	-1.14	-2.95	-0.59	-2.44
TFP	-0.58	-1.77	-0.81	-2.28	-0.23	-0.97
IPG	-0.70	-2.29	-1.07	-2.90	-0.37	-2.04
$TERM$	-0.48	-1.67	-1.00	-2.75	-0.52	-2.02
DEF	-0.43	-1.56	-1.05	-2.93	-0.62	-2.83
UI	-0.54	-1.62	-0.93	-3.13	-0.39	-1.76
DEI	-0.73	-2.11	-0.91	-3.38	-0.18	-0.77
VOL	-0.36	-1.61	-1.24	-3.16	-0.88	-3.38
MKT	-0.08	-0.39	-1.23	-2.90	-1.15	-3.34
LAB	-0.69	-2.29	-1.30	-3.43	-0.61	-1.86
$Ave1$	-0.49	-2.02	-1.13	-3.09	-0.64	-3.64
$Ave2$	-0.48	-1.96	-1.10	-3.07	-0.62	-3.89
$Ave3$	-0.51	-1.97	-1.07	-3.15	-0.55	-4.26

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} \quad = \quad a + bS_{t-1} + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, and S_t is the level of the BW sentiment index. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.6: Predictive Regressions for Benchmark-Adjusted Returns on Long-Short Strategies

	Low Risk		High Risk		High $-$ Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.07	-0.43	-0.43	-3.03	-0.36	-1.67
TFP	-0.10	-0.71	-0.16	-1.02	-0.06	-0.28
IPG	-0.11	-0.77	-0.39	-2.58	-0.29	-1.70
$TERM$	0.09	0.76	-0.39	-2.31	-0.48	-2.09
DEF	0.10	0.79	-0.36	-2.32	-0.46	-2.11
UI	0.06	0.53	-0.33	-2.39	-0.39	-1.80
DEI	-0.07	-0.69	-0.38	-2.28	-0.30	-1.53
VOL	0.03	0.25	-0.43	-3.13	-0.46	-2.48
MKT	0.08	0.74	-0.41	-3.33	-0.48	-2.58
LAB	-0.17	-1.27	-0.64	-3.08	-0.47	-1.68
$Ave1$	-0.06	-0.81	-0.41	-3.69	-0.36	-2.92
$Ave2$	-0.02	-0.27	-0.40	-3.72	-0.38	-3.40
$Ave3$	-0.02	-0.26	-0.39	-3.81	-0.38	-3.71

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} \quad = \quad a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the BW sentiment index, and MTK_t, SMB_t, and HML_t are the Fama-French 3 factors. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.7: Investor Sentiment Changes and Macro-Factor-Based Portfolios

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	2.12	5.94	3.55	8.20	1.44	4.91
TFP	2.26	6.02	3.06	6.69	0.79	2.39
IPG	2.64	5.86	3.74	7.09	1.10	3.50
$TERM$	2.49	7.01	2.98	5.77	0.48	1.41
DEF	2.43	5.75	3.23	8.28	0.80	2.19
UI	2.47	7.30	2.69	6.20	0.22	0.55
DEI	3.03	6.27	2.64	5.93	-0.39	-1.21
VOL	1.76	6.32	3.88	7.17	2.13	5.33
MKT	0.22	0.89	4.05	7.92	3.84	6.27
LAB	2.16	8.03	3.43	6.02	1.27	2.15
$Ave1$	1.86	7.52	3.62	7.49	1.76	5.34
$Ave2$	2.01	7.37	3.49	7.51	1.48	5.23
$Ave3$	2.16	7.45	3.32	7.32	1.17	4.42

The table reports point estimates of b, along with t-statistics in the regression

$$R_{i,t} \quad = \quad a + b\Delta S_t + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, ΔS_t is the change of investor-sentiment index of Baker and Wurgler (2006). The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. Both levels and changes in sentiment are taken directly from Baker and Wurger's online dataset. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.8: Sentiment Change as a Factor

Panel A: Returns across Two Sentiment Regimes

Low Risk			High Risk			High − Low		
High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low
0.42	0.53	-0.10	-0.78	0.88	-1.67	-1.21	0.35	-1.56
(1.24)	(1.88)	(-0.24)	(-1.14)	(1.50)	(-1.81)	(-2.19)	(0.77)	(-2.20)

Panel B: $R_{i,t} = a + bS_{t-1} + \epsilon_t$

Low Risk			High Risk			High − Low		
a	b	R^2	a	b	R^2	a	b	R^2
0.48	-0.07	0.02	0.09	-1.36	1.92	-0.39	-1.30	2.51
(2.13)	(-0.29)		(0.21)	(-2.87)		(-1.11)	(-3.71)	

Panel C: Regression of Market Excess Returns on Lagged Sentiment

$R_t = a + bS_{t-1} + \epsilon_t$			$R_t = a + b^+S^+_{t-1} + b^-S^-_{t-1} + \epsilon_t$			
a	b	R^2	a	b^+	b^-	R^2
0.43	-0.32	0.49	0.81	-0.82	0.21	1.08
(2.05)	(-1.44)		(2.96)	(-2.54)	(0.56)	

Panels A and B of the table report the results for excess returns of portfolios based on their sensitivity to changes in sentiment. Panel A reports the average returns across two sentiment regimes, as classified based on the median level of the BW sentiment index. Panel B reports the results for the regression of portfolio returns on lagged sentiment. Panel C reports the predictive regression results of market excess returns, R_t, on the lagged sentiment variables, S_{t-1}, S^+_{t-1}, and S^-_{t-1}. Here, $S^+_t \equiv max(S_t, 0)$ and $S^-_t \equiv min(S_t, 0)$. Both levels and changes in sentiment are taken directly from Baker and Wurger's online dataset. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. The R-squared is reported in percentage.

Table 1.9: Predictive Regressions Controlling for Additional Macro Variables

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.66	-2.39	-1.45	-3.87	-0.80	-3.47
TFP	-0.77	-2.39	-1.07	-2.93	-0.30	-1.14
IPG	-0.87	-2.93	-1.29	-3.57	-0.41	-2.22
$TERM$	-0.71	-2.53	-1.13	-3.10	-0.42	-1.63
DEF	-0.68	-2.49	-1.24	-3.56	-0.57	-2.44
UI	-0.78	-2.45	-1.08	-3.80	-0.30	-1.31
DEI	-0.94	-2.75	-0.98	-3.64	-0.04	-0.16
VOL	-0.44	-2.08	-1.56	-4.01	-1.13	-3.87
MKT	-0.20	-1.05	-1.45	-3.50	-1.25	-3.33
LAB	-0.89	-2.99	-1.49	-3.61	-0.59	-1.48
$Ave1$	-0.64	-2.74	-1.38	-3.79	-0.75	-3.66
$Ave2$	-0.65	-2.76	-1.33	-3.74	-0.68	-3.70
$Ave3$	-0.69	-2.78	-1.27	-3.81	-0.58	-3.76

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} = a + bS_{t-1} + \sum_{j=1}^{5} m_j X_{j,t-1} + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the BW sentiment index, and $X_{1,t}, \ldots, X_{5,t}$ are five additional macro variables not used by Baker and Wurgler (2006) when removing macro-related variation in sentiment: the default premium, the term premium, the real interest rate, the inflation rate, and the wealth-consumption ratio. The growth in industrial production; the real growth in durable, nondurable, and services consumption; the growth in employment; and a flag for NBER recessions are already controlled by Baker and Wurgler (2006). The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.10: Predictive Regressions Using Michigan Sentiment Index

	Low Risk		High Risk		High $-$ Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.22	-0.48	-1.04	-2.03	-0.82	-2.58
TFP	-0.34	-0.87	-0.57	-1.06	-0.22	-0.59
IPG	-0.42	-0.93	-0.46	-0.81	-0.04	-0.15
$TERM$	-0.26	-0.55	-1.09	-2.11	-0.82	-2.29
DEF	-0.38	-0.95	-1.00	-2.17	-0.62	-1.74
UI	-0.41	-1.03	-0.94	-2.01	-0.54	-1.64
DEI	-0.33	-0.73	-0.90	-1.79	-0.58	-1.87
VOL	-0.38	-1.12	-0.94	-1.70	-0.56	-1.69
MKT	-0.05	-0.27	-0.90	-1.43	-0.84	-1.35
LAB	-0.26	-0.70	-1.20	-1.94	-0.94	-2.13
$Ave1$	-0.28	-0.87	-0.85	-1.55	-0.57	-1.98
$Ave2$	-0.29	-0.84	-0.90	-1.73	-0.61	-2.52
$Ave3$	-0.31	-0.87	-0.90	-1.78	-0.60	-2.72

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} = a + bS_{t-1} + \sum_{j=1}^{5} m_j X_{j,t-1} + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the Michigan sentiment index in month t, and $X_{1,t}, \ldots, X_{5,t}$ are five additional macro control variables: the default premium, the term premium, the real interest rate, the inflation rate, and the wealth-consumption ratio. The growth in industrial production; the real growth in durable, nondurable, and services consumption; the growth in employment; and a flag for NBER recessions are already controlled when constructing the Michigan sentiment index following the approach of Baker and Wurgler (2006). The results for three average portfolios are also reported. The sample period is from 1978:1 to 2010:12, during which the monthly Michigan sentiment index is available. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

Table 1.11: Spurious Predictive Regression Critique

Panel A: Distribution of the t-statistics from two-regime simulations

	mean	2.5%	5%	50%	95%	97.5%
CON	-0.019	-2.117	-1.742	-0.020	1.759	2.005
TFP	0.026	-1.929	-1.627	-0.030	1.855	2.166
IPG	0.009	-1.913	-1.568	0.047	1.648	1.850
TERM	-0.053	-2.752	-2.347	-0.089	2.196	2.769
DEF	-0.027	-1.974	-1.756	0.024	1.525	1.888
UI	-0.012	-2.415	-2.001	-0.038	2.190	2.611
DEI	-0.019	-2.203	-1.871	-0.043	1.906	2.291
VOL	0.001	-1.993	-1.700	0.018	1.557	1.809
MKT	0.032	-1.723	-1.404	0.016	1.469	1.654
LAB	-0.009	-2.104	-1.764	0.013	1.719	2.032
Ave1	0.011	-1.696	-1.375	0.036	1.341	1.728
Ave2	-0.006	-1.926	-1.677	0.034	1.551	1.846
Ave3	-0.011	-2.301	-1.894	-0.016	1.789	2.111

Panel B: The fraction of simulations with all 10 t-stats less than a certain value

	0	-0.5	-1	-1.25	-1.5
Two-Regime	0.028	0.002	0.001	0.001	0
Continuous Sentiment	0.034	0.002	0	0	0

First, we simulate artificial sentiment index by

$$s_{t+1} = \rho s_t + \epsilon_{t+1},$$

where $s_0 = 0$, $\rho = 0.984$, and $\epsilon \sim N(0,1)$. The simulated sentiment has equal length with the true BW index. Then, we perform both the two-regime sentiment analysis as in Table 3 and the predictive regression analysis as in Table 5 by using the simulated sentiment index. The corresponding t-statistics for the last column of Table 3 and Table 5 are collected. We repeat the above procedure for 1,000 times to obtain 1,000 by 13 t-statistics panel for the last column of Table 3 and Table 5. Panel A reports the 2.5%, 5%, 50%, 95%, and 97.5% quantiles of the t-statistics for the two-regime analysis. To save space, the corresponding results for predictive regression analysis are omitted. Panel B reports the fraction of simulations with all 10 t-statistics for individual macro-related factor simultaneously less than a certain value for both the two-regime analysis and the predictive regression analysis.

Table 1.12: Predictive Regressions Controlling for Additional Mechanisms

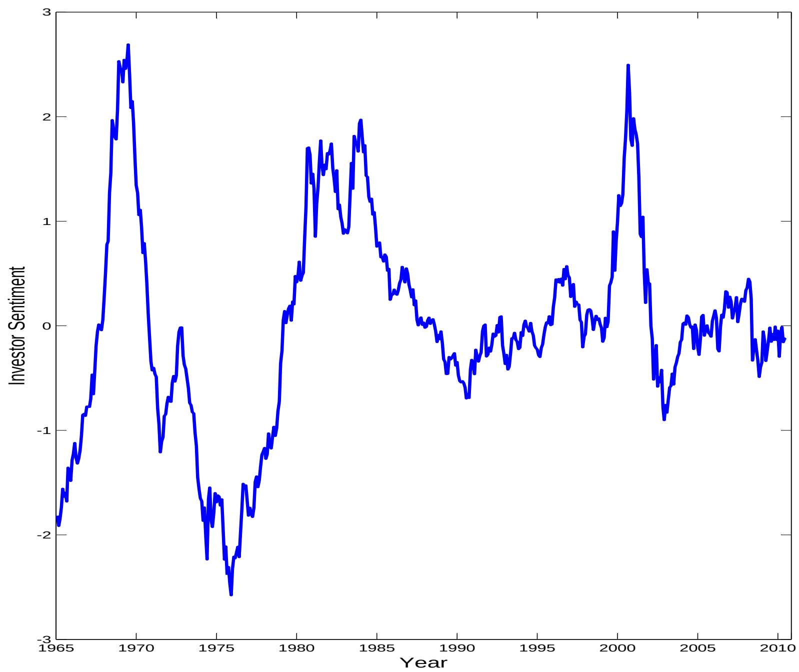
	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-2.43	-2.13	-3.30	-2.24	-0.88	-1.04
TFP	-0.75	-0.68	-3.32	-2.43	-2.57	-2.94
IPG	-2.59	-1.99	-3.87	-2.31	-1.28	-1.71
$TERM$	-2.92	-1.96	-2.22	-1.61	0.70	0.74
DEF	-1.60	-1.28	-2.85	-2.36	-1.25	-1.09
UI	-2.18	-1.85	-2.69	-1.99	-0.51	-0.51
DEI	-2.53	-1.71	-2.79	-1.85	-0.25	-0.29
VOL	-0.90	-0.98	-4.41	-2.56	-3.51	-3.19
MKT	-0.05	-0.08	-4.18	-2.28	-4.13	-2.18
LAB	-1.39	-1.27	-4.70	-2.76	-3.31	-2.88
$Ave1$	-1.35	-1.51	-3.97	-2.51	-2.61	-3.03
$Ave2$	-1.58	-1.60	-3.61	-2.46	-2.03	-3.00
$Ave3$	-1.73	-1.68	-3.43	-2.39	-1.70	-2.82

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} \quad = \quad a + bS_{t-1} + \sum_{j=1}^{4} m_j X_{j,t-1} + cTED_{t-1} + dInf_{t-1} + eDAG_{t-1} + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the BW sentiment index, and $X_{1,t}, \ldots, X_{4,t}$ are four additional macro variables not used by Baker and Wurgler (2006) when removing macro-related variation in sentiment: the default premium, the term premium, the real interest rate and the wealth-consumption ratio. The growth in industrial production; the real growth in durable, nondurable, and services consumption; the growth in employment; and a flag for NBER recessions are already controlled by Baker and Wurgler (2006). We controlled alternative mechanisms by including TED (the 3-month rate difference between LIBOR and treasury bill rate), the inflation rate Inf, and aggregate disagreement DAG (beta-weighted aggregate disagreement). The results for three average portfolios are also reported. The sample period is from 1986:01 to 2010:12 for all portfolios. All t-statistics are robust to heteroskedasticity.

Figure 1.1: The Investor Sentiment Index



The sentiment index spans from 1965:07 to 2010:12. It is constructed as the first principal component of six sentiment proxies. The six individual proxies are the closed-end fund discount, the NYSE share turnover, the number and average of first-day returns on IPOs, the equity share in new issues, and the dividend premium. To control for macro conditions, the six raw sentiment measures are regressed on the growth in industrial production, the growth in durable consumption, the growth in nondurable consumption, the growth in service consumption, the growth of employment, and a dummy variable for NBER recessions.

Chapter 2

Capital Misallocation and Financial Market Frictions: Empirical Evidence from Equity Cost of Financing

2.1 Introduction

The output fell dramatically after the 2008 crisis and it remains below its prior growth path even eight years after the crisis.[1] One plausible explanation for such persistent stagnation is that productive resources move too slowly to the most productive firms and hence, the total output produced by per unit of capital and labor is reduced. Indeed, there is a huge literature on such "capital misallocation" and how it can lead to aggregate output loss. In a seminal paper, Hsieh and Klenow (2009) document that

[1] See Hall (2016)

the misallocation of capital and labor can reduce U.S. total productivity by about 30%.

It is more important to understand the mechanism of the misallocation and the relevant remedies to correct the misallocation. Financial market frictions can be one possible channel in which less efficient firms reap the funding which should have gone to more productive firms. If this were the case, productive firms do not have sufficient financing to acquire the optimal level of production inputs. In this paper, I try to answer the question how much of the total factor productivity (TFP) loss is led to by the misallocation arising from the financial market frictions.

My paper uses a two-period TFP accounting framework to map the dispersion in firm's borrowing costs of capital into TFP losses. Financial frictions show up as heterogeneous borrowing costs for the different firms. In particular, when high productivity firms have a high borrowing cost relative to low productivity firms, they cannot acquire the optimal capital as what they would like to obtain without any financial friction. Hence, the expected marginal product of capital (MPK) would differ between the high and low productivity firms, and the extent of difference characterizes the magnitude of the misallocation. To understand the impact of the financial friction on output, I connect the dispersion in firm's borrowing costs with TFP losses.

My major contribution in this paper is to demonstrate that the timing of the investment decision matters for the measurement of the "actual" TFP loss, which is the fraction to be corrected in practice. In Hsieh and Klenow (2009), firms can observe their productivity shocks before making the investment decision. The extent of misallocation is manifested in the dispersion in the realized marginal product. In reality, firms make investment and hiring decision before the productivity shocks realize. It is more meaningful to examine the dispersion of marginal product ex ante, which is how much TFP can be increased by when the financial frictions are alleviated. Then, the paper links firm's expected profitability to firm's borrowing cost and by mapping the dispersion in firm's equity cost of capital into TFP losses.

I apply the accounting framework, adopted from Gilchrist et al. (2013), to a panel of U.S. manufacturing firms from Compustat database. Despite fairly large and persistent differences in borrowing costs across firms, my estimates imply moderate losses in TFP due to financial frictions - on the order of 5 percent of TFP in the U.S. manufacturing sector.[2] This finding of TFP losses is slightly greater than that in Gilchrist et al. (2013) (on the order of 3.5 percent), and is much smaller than that in Hsieh and Klenow (2009).

My result can be obtained directly from the log-normal approximation and information on the dispersion of individual borrowing costs across firms. Besides, I also try to relax the log-normal distribution and infer TFP losses using the joint distribution of sales and borrowing costs. I find that the estimated losses under this approach closely match those obtained under the assumption of log-normality. This finding suggests both the robustness of my results and its applicability to a broader environment where firm-level data on the joint distribution of sales and borrowing costs may not be available.

I also compute TFP losses over time and within different groups of firms. First, TFP losses induced by financial frictions are countercyclical and are stronger (over 5 percent) during the two recent economic crises. This result provides evidence that the disruption of financial sector can distort the allocation of capital and thus reduce output. Second, TFP losses in the more financially constrained firms are at least 50% more severe than those in the less constrained counterparts (on the order of 6% versus 4%).

My paper also compares the dispersion in the equity cost of capital to the dispersion in the realized marginal product of capital, an approach consistent with the methodology of Hsieh and Klenow (2009). I find that the latter measure overstates the degree of

[2] I use several measures for equity cost of capital: implied cost of capital, CAPM model and Fama-French 3 factor model. I also use weighted average cost of capital as a more precise estimate of firm's cost of borrowing.

resource misallocation by a factor of three as compared with the dispersion measure using equity cost of capital. Indeed, the dispersion in realized MPK should be greater since it can capture both financial frictions and other sources of frictions such as policy-induced taxes, fixed production costs, and other measurement-related issues.

My paper is related to a broad literature on resource misallocation and productivity.[3] Hsieh and Klenow (2009) document that misallocation can create a large loss to the productivity for US, China, and India. By using census data, they examine whether plant's age, size, region and ownership can explain the variation in the marginal product; but, find little evidence. Eisfeldt and Rampini (2006) show that reallocation of capital accounts for about a quarter of firm's new investment, which suggests the reallocation of used capital is material. They also document that reallocation of capital is procyclical, while the benefit to reallocation is countercyclical.

The closest paper to mine is Gilchrist et al. (2013). They also study the question that how much of TFP loss is due to financial friction. They use firm-specific interest rate implied by the corporate bond as the borrowing cost. They find that the TFP loss, arising from resource misallocation due to financial friction is a modest 1.75%. My paper complements their paper by using an alternative financing cost: the cost of equity capital. More firms use equity than corporate bond: of all the sample observations, I have over 4000 firms in my sample while Gilchrist et al. (2013) only have 496 firms. Hence, cost of equity is worthwhile to consider when doing this empirical exercise.

In order to understand the recent financial crisis, researchers have studied the implication of credit market shocks, together with collateral constraint, on the business fluctuation (See Jermann and Quadrini (2012) and Khan and Thomas (2013)). Firms cannot borrow enough capital when their collateral constraint is hit by a negative credit

[3] Hopenhayn (2014) is an excellent survey on misallocation and aggregate productivity.

market shock; hence, there is a distortion in the distribution of capital during the recession. My paper shows that the dispersion of marginal capital (as estimated by the dispersion in the borrowing costs) increases during the recent recession, which lends indirect support to these papers.

The rest of the paper is organized as follows. I set up the accounting framework to estimate the TFP loss due to firm's heterogeneous borrowing costs in section 2. Results are illustrated and conclusions are made in section 3 and 4 respectively.

2.2 The Accounting Framework

In this section, I introduce the accounting framework that maps the dispersion in firm-specific borrowing costs into the TFP losses. The framework, which is adopted from Gilchrist et al. (2013) and Midrigan and Xu (2014), features the heterogenous borrowing costs, faced by a continuum of firms with decreasing return to scale production technology.

2.2.1 A simple two-period model

Assume there is a continuum of producers in the economy. Firms are endowed with capital $K_{0,i}$, and productivity $A_{0,i}$. Given a borrowing cost r, firms choose tomorrow's capital and labor at period 0. Every firm has a decreasing return to scale production technology: $Y_i = A_i^{1-\eta}(K_i^{1-\alpha}L_i^{\alpha})^{\eta}$, where $0 < \eta < 1$ is the degree of decreasing return to scale. Firm i's problem at date 0 is

$$\max_{K_{1,i},L_{1,i}} : Y_{0,i} - I_{0,i} - WL_{1,i} + \frac{1}{1+r}\mathbb{E}_0[Y_{1,i} + (1-\delta)K_{1,i}]$$
$$\text{s.t. } K_{1,i} = I_{0,i} + (1-\delta)K_{0,i}.$$

Under a frictionless economy, every firm faces the same borrowing cost r. Firm i's first order condition (FOC) implies that the expected marginal product of capital (and labor) equals its marginal cost of one unit of external financing.

$$\mathbb{E}_0[MPK_i] \equiv \mathbb{E}_0[\frac{\eta(1-\alpha)Y_{1,i}}{K_{1,i}}] = r + \delta \qquad [K_1]$$

$$\mathbb{E}_0[MPL_i] \equiv \mathbb{E}_0[\frac{\eta\alpha Y_{1,i}}{L_{1,i}}] = (1+r)W \qquad [L_1]$$

The borrowing cost r and wage W are exogenous. Without any friction, the expected marginal product of capital and labor should be equalized across firms. Hence, there is misallocation of productive inputs *when the expected marginal product of capital or labor differs across firms.*

Firm i's F.O.C suggests that its share of capital (and labor) is directly proportional to the expectation of its future productivity.

$$\frac{K_{1,i}}{K_1} = \frac{\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}}{\sum_i \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}} \left(= \frac{L_{1,i}}{L_1}\right),$$

where K_1 and L_1 are the aggregate capital and labor at date 1. The ratio between the capital of two different firms is $\frac{\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}}{\mathbb{E}_0[A_{1,j}^{1-\eta}]^{\frac{1}{1-\eta}}}$, which indicates that the firm with a high expected productivity would invest up to the optimal level until its expected marginal product is equal to other firms in the economy. The aggregate output at date 1 is

$$\begin{aligned} Y_1 = \int Y_{1,i} di &= \int A_{1,i}^{1-\eta} \frac{\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{\eta}{1-\eta}}}{\left(\sum_i \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}\right)^{\eta}} K_1^{(1-\alpha)\eta} L_1^{\alpha\eta} di \\ &\approx TFP_E K_1^{(1-\alpha)\eta} L_1^{\alpha\eta}, \end{aligned}$$

where the **efficient TFP** in the two-period framework is[4]

$$TFP_E = \left(\int \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di \right)^{1-\eta}. \tag{2.1}$$

Next, I add financial frictions in the above framework: firm's borrowing costs are heterogenous as $1 + r + \tau_i$. Firm's F.O.C are

$$\mathbb{E}_0[\frac{\eta(1-\alpha)Y_{1,i}}{K_{1,i}}] = r_i + \delta; \qquad [K_1] \tag{2.2}$$

$$\mathbb{E}_0[\frac{\eta\alpha Y_{1,i}}{L_{1,i}}] = (1 + r_i)W, \qquad [L_1] \tag{2.3}$$

where $r_i = r + \tau_i$. A high expected productivity firm may also have a high borrowing cost, which weakens its ability to obtain sufficient capital as the firm would like to. The firm-specific borrowing cost introduces a wedge in the optimal level of the expected marginal product of capital and labor. As will be shown, the TFP loss with respect to TFP_E is determined by the dispersion of these wedges.

Solving for the capital yields

$$\eta(1-\alpha)\mathbb{E}_0[A_{1,i}^{1-\eta}] \left(\frac{K_{1,i}}{L_{1,i}} \right)^{-\alpha\eta} K_{1,i}^{\eta-1} = r_i + \delta.$$

which implies the optimal capital and labor:

$$K_{1,i} = c_K[(1 + r_i)^{-\frac{\alpha\eta}{1-\eta}} (r_i + \delta)^{-\frac{1-\alpha\eta}{1-\eta}}]\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}$$

$$L_{1,i} = c_L[(1 + r_i)^{-\frac{1-(1-\alpha)\eta}{1-\eta}} (r_i + \delta)^{-\frac{(1-\alpha)\eta}{1-\eta}}]\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}$$

[4] True TFP is determined by the realized shocks. $TFP = TFP_E + \sum_i (A_{1,i}^{1-\eta} - \mathbb{E}_0[A_{1,i}^{1-\eta}]) \frac{\mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{\eta}{1-\eta}}}{\left(\sum_i \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}\right)^{\eta}}$. Given that firm's specific productivity follows a finite Markov chain, the residual should converge to zero when firms are in the stationary distribution.

for some positive constants c_K and c_L. I denote capital and labor wedges as follows:

$$w_i^k \equiv (1+r_i)^{-\frac{\alpha\eta}{1-\eta}}(r_i+\delta)^{-\frac{1-\alpha\eta}{1-\eta}},$$
$$w_i^l \equiv (1+r_i)^{-\frac{1-(1-\alpha)\eta}{1-\eta}}(r_i+\delta)^{-\frac{(1-\alpha)\eta}{1-\eta}};$$

then the optimal input choices are proportional to firm's expected productivity, adjusted for firm-specific differences in their borrowing costs:

$$K_{1,i} = c_K w_i^k \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}},$$
$$L_{1,i} = c_L w_i^l \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}.$$

Define the aggregate capital and labor

$$K_1 = c_K \int w_i^k \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di, \quad \text{and} \quad L_1 = c_L \int w_i^l \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di.$$

The aggregate output at date 1 can be expressed as

$$Y_1 = \int Y_{1,i} di = c_K^{(1-\alpha)\eta} c_L^{\alpha\eta} \int A_{1,i}^{1-\eta} \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{\eta}{1-\eta}} w_i^\eta di,$$

where the aggregate wedge is defined by $w_i = (w_i^k)^{1-\alpha}(w_i^l)^\alpha$.

Total factor productivity with the financial friction is measured as aggregate output relative to a geometrically-weighted average of aggregate capital and labor:

$$TFP_F = \frac{Y_1}{L_1^{\alpha\eta} K_1^{(1-\alpha)\eta}} \approx \frac{\int w_i^\eta \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di}{(\int w_i^l \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di)^{\alpha\eta} (\int w_i^k \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di)^{(1-\alpha)\eta}}.$$

TFP loss is defined by the log-difference between TFP_E and TFP_F. In the next subsection, two methods are applied to approximate the TFP loss.

2.2.2 TFP Loss Approximation

TFP Loss Approximation: Method I

Denote $\tilde{A}_{1,i} = \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}}$. By assuming a joint log-normal distribution between the productivity and the wedges,

$$\begin{bmatrix} \log \tilde{A}_{1,i} \\ \log w_i^l \\ \log w_i^k \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} a \\ w_l \\ w_k \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{a,w_l} & \sigma_{a,w_k} \\ \sigma_{a,w_l} & \sigma_{w_l}^2 & \sigma_{w_l,w_k} \\ \sigma_{a,w_k} & \sigma_{w_l,w_k} & \sigma_{w_k}^2 \end{bmatrix}\right),$$

TFP_E and TFP_F can be approximated by the distribution of the sample mean of the productivity and the wedges.

The second-order approximation of efficient TFP is:

$$\begin{aligned} TFP_E &= \left(\int \mathbb{E}_0[A_{1,i}^{1-\eta}]^{\frac{1}{1-\eta}} di\right)^{1-\eta} = \left(\int \tilde{A}_{1,i} di\right)^{1-\eta}, \\ \log(TFP_E) &= (1-\eta)\left[a + \frac{\sigma_a^2}{2}\right]. \end{aligned}$$

The second-order approximation of TFP with the financial friction:

$$\begin{aligned} \log TFP_F &= \log\left(\int w_i^\eta \tilde{A}_{1,i} di\right) - (1-\alpha)\eta \log\left(\int w_i^k \tilde{A}_{1,i} di\right) - \alpha\eta \log\left(\int w_i^l \tilde{A}_{1,i} di\right) \\ \log TFP_F &= (1-\eta)\left[a + \frac{\sigma_a^2}{2}\right] - \frac{\eta\alpha(1-\eta\alpha)}{2}\sigma_{w_l}^2 - \frac{\eta(1-\alpha)(1-\eta(1-\alpha))}{2}\sigma_{w_k}^2 \\ &\quad + \eta^2\alpha(1-\alpha)\sigma_{w_k}\sigma_{w_l}. \end{aligned}$$

The relative TFP loss that is attributable to resource misallocation caused by the dispersion in firm's borrowing costs is given by

$$\log\left(\frac{TFP_E}{TFP_F}\right) = \frac{\eta\alpha(1-\eta\alpha)}{2}\sigma_{w_l}^2 + \frac{\eta(1-\alpha)(1-\eta(1-\alpha))}{2}\sigma_{w_k}^2 - \eta^2\alpha(1-\alpha)\sigma_{w_k}\sigma_{w_l}. \quad (2.4)$$

The first method approximates the TFP loss by the dispersion in the wedges of borrowing cost.

To map the dispersion in firm's borrowing costs into TFP losses due to the misallocation, the first approximation method uses the Taylor expansion. Given the definition of log wedges:

$$\begin{aligned}
\log w_i^k &= -\frac{\alpha\eta}{1-\eta}\log(1+r_i) - \frac{1-\alpha\eta}{1-\eta}\log(r_i+\delta), \\
\log w_i^l &= -\frac{1-(1-\alpha)\eta}{1-\eta}\log(1+r_i) - \frac{(1-\alpha)\eta}{1-\eta}\log(r_i+\delta);
\end{aligned}$$

the first-order Taylor expansion of the log wedges around $r = \bar{r}$ is

$$\begin{aligned}
\log(w_i^k) &\approx -\frac{1}{1-\eta}\left[\alpha\eta\frac{1}{1+\bar{r}} + (1-\alpha\eta)\frac{1}{\bar{r}+\delta}\right](r_i-\bar{r}), \\
\log(w_i^l) &\approx -\frac{1}{1-\eta}\left[(1-(1-\alpha)\eta)\frac{1}{1+\bar{r}} + (1-\alpha)\eta\frac{1}{\bar{r}+\delta}\right](r_i-\bar{r}).
\end{aligned}$$

From equation (2.4), I can then approximate the relative TFP loss as

$$\log\left(\frac{TFP_E}{TFP_F}\right) = \left(\frac{\eta(1-\alpha)[1-\eta(1-\alpha)]}{2} + \frac{\alpha\eta(1-\alpha\eta)}{2}\left(\frac{\sigma_{w_l}}{\sigma_{w_k}}\right)^2 - \eta^2\alpha(1-\alpha)\frac{\sigma_{w_l}}{\sigma_{w_k}}\right)\sigma_{w_k}^2, \tag{2.5}$$

where

$$\sigma_{w_k} = \frac{1}{1-\eta}\left[\alpha\eta\frac{1}{1+\bar{r}} + (1-\alpha\eta)\frac{1}{\bar{r}+\delta}\right]\sigma_r \tag{2.6}$$

$$= C_{w_k}\sigma_\tau \tag{2.7}$$

From equation (2.5), the TFP loss includes three terms: the first reflects the direct effect of variation in w_k on the resource misallocation. The second term captures the direct effect of variation in w_l, while the third term is due to the covariance between w_l

and w_k.

And, the variation in w_k is approximately proportional to the dispersion in firm-specific borrowing cost σ_r in equation (2.6). Indeed, equation (2.7) indicates the measurement of the dispersion in the extent of the financial friction embedded in τ_i's.

TFP Loss Approximation: Method II

I can also use firm's sale data from Compustat and estimate the TFP loss without assuming a log-normal distribution between the productivity and the wedges. This is a more direct way to estimate the TFP loss. Given that I have reasonable proxies of firm's borrowing cost, I can impute firm's capital and labor:

$$K_{1,i} = \frac{(1-\alpha)\eta Y_{1,i}}{r_i + \delta} \quad \text{and} \quad L_{1,i} = \frac{\alpha\eta Y_{1,i}}{(1+r_i)W}.$$

The realized TFP is

$$TFP_F = \frac{Y_1}{K_1^{(1-\alpha)\eta} L_1^{\alpha\eta}},$$

where $Y_1 = \frac{1}{N}\sum_i Y_{1,i}$, $K_1 = \frac{1}{N}\sum_i K_{1,i}$, and $L_1 = \frac{1}{N}\sum_i L_{1,i}$.

Firm-level productivity can be imputed as well:

$$A_{1,i} = \frac{Y_{1,i}}{K_{1,i}^{(1-\alpha)\eta} L_{1,i}^{\alpha\eta}}.$$

Hence, the efficient TFP under this case is:

$$TFP_E = \left(\sum_i A_{1,i}\right)^{(1-\eta)}$$

And, the relative TFP loss due to resource misallocation

$$\text{Relative TFP loss} = \log\left(\frac{TFP_E}{TFP_F}\right).$$

2.2.3 Methods to compute equity cost of capital

I use equity cost of capital as firm-specific borrowing cost. First, equity cost of capital, which contains investor's expectation of firm's future profits, serves the goal to be a proxy for expected marginal product. Second, equity financing is an important method for firms to finance asset growth. Fama and French (2005) document that firms frequently issue equity, and equity issues are quantitatively important. Covas and Den Haan (2011) find that net issues of equity finance an average of 21.1% in asset growth for Compustat firms.

I use two estimators for firm's equity cost of capital: implied cost of capital (ICC) and factor-based pricing model (CAPM and Fama-French three factor model). The implied cost of capital (ICC) is the discount rate that equates the present value of expected future dividends to the current stock price. One appealing feature of the ICC as a proxy for expected return is that it does not rely on noisy realized asset return. And, it is a forward-looking measure, which serves the purpose to proxy the expected marginal product of capital. The ICC has been applied to resolve the failure of intertemporal relation between the time series of equity return and volatility (Pástor et al. (2008)). In addition, some cross-sectional anomalies can be explained when ICC is used as expected return (Chava and Purnanandam (2010)). So, ICC is a reasonable proxy for the equity cost of capital. I also use CAPM and Fama-French 3 factor model to estimate cost of capital as a standard procedure in the literature.

One caveat is that the conditional expectation might contain risk component; firm's getting a rather high borrowing cost might as well be that the lenders believe they are too risky and need to be charged at a high rate. Hence, a large dispersion in the the equity cost of capital can simply be a high variation in firm's risk, which doesn't relate to resource misallocation. To address this concern, I regress the measures of cost of capital, and use the intercept term α as a proxy for the borrowing cost that is relevant only to the financial friction. The results show that TFP losses due to financial friction are from 1.02% to 2.4%.

I compute the ICC using the discounted cash flow model of equity valuation. In this approach, the expected return on a stock is computed as the internal rate of return that is equal to the present value of free cash flows to the current price. The stock price $P_{i,t}$ of firm i at year t is given by

$$P_{i,t} = \sum_{s=1}^{\infty} \frac{E_t[FCFE_{i,t+s}]}{(1 + r_{i,e})^s}, \tag{2.8}$$

where $FCFE_{i,t+s}$ is the free cash flow to equity of firm i in year $t + s$; E_t is the expectation operator conditional on the information at year t; and $r_{i,e}$ is the ICC.

I use consensus forecasts from the I/B/E/S database to estimate the future earnings. Consistent with the prior literature, I assume that the consensus forecast is a good proxy of investor expectation. I explicitly forecast future earnings for the first fifteen years and capture the effect of all remaining cash flows using a terminal value computation. I obtain earnings forecasts for years $t + 1$ and $t + 2$ using one- and two-year ahead consensus forecasts. For the subsequent years, I project earnings based on the long-term growth rate, which is also obtained from I/B/E/S database. The calculation of ICC follows closely that in Pástor et al. (2008), which is detailed in the appendix.

One concern of using ICC is coverage. The IBES analyst data are only available after the late 1970s, and small firms and financially constrained firms are underrepresented (Hou et al. (2012)). And, some firms can have negative earning forecasts, which make equation (2.8) insolvable. (This accounts for about 10% of sample, i.e., 4200 firm-year observations.) Hence, I also use factor-based pricing model (CAPM and Fama-French 3 factor model) to estimate the equity cost of capital.

2.3 Results

I use the accounting framework to provide some estimates of TFP loss for the U.S. manufacturing sector (the four-digit standard industry classification code between 2011 and 3999) arising from financial frictions. Specifically, I use the information on the dispersion of firm-specific cost of capital to calculate the implied TFP loss, an approach that relies on the assumption of log-normality. And, I utilize both firm-level cost of capital and sale to perform another calculation of TFP loss. In most of the exercises, I set the depreciation rate $\delta = 0.06$, the labor share $\alpha = 2/3$, and the degree of decreasing returns to scale $\eta = 0.85$, values that are standard in the literature.

The results in Table 1 indicate that the loss in U.S. manufacturing TFP due to resource misallocation arising from financial market frictions is relatively modest as compared to Hsieh and Klenow (2009). The losses implied by my first method, using ICC, are about 3.2 percent for the manufacturing sector as a whole and for its two main subsectors: durable good producers and nondurable good producers. Meantime, the second TFP losses, using ICC, are around 4.1 percent for the manufacturing sector as a whole; as before, the estimated losses are very similar across the two subsectors. From an economic perspective, both methods imply TFP losses that are sufficiently close in magnitude, which suggests that the log-normal approximation provides a reasonable estimate of the TFP losses in the case where only information on the dispersion of borrowing cost across firms is available. When CAPM and FF3 factor model are used to calculate the equity cost of capital, the TFP losses become slightly larger and range from 5 to 6.4 percent.

I further explore the impact of misallocation on output losses for the firms with different extent of financial constraint. The literature on misallocation has emphasized that the more productive firms are more financially constrained and cannot obtain sufficient capital. Hence, financially constrained firms are expected to suffer more from the misallocation. Utilizing the TFP accounting framework, I will examine this implication.

One of the major difficulties of the empirical analysis is how to distinguish firms that are financially constrained from those that are not. The finance literature provides various approaches to proxy the severity of financial constraints a firm is subject to. However, many of them rely on endogenous financial choices that may not have a straightforward relation to constraints. According to Hadlock and Pierce (2009), two firm characteristics that do appear to be closely related to financial constraints are firm size and age. These classification schemes are in accordance with the conventional wisdom that, in reality, financial constraints become less likely to be binding as young and small firms start to mature and grow.[5]

In light of Hadlock and Pierce's finding, I adopt two approaches as our main classification schemes to sort our sample into financially constrained and unconstrained groups. First, I follow the convention of using firm size as a proxy for financial market access: i.e., smaller firms are more likely to be constrained. In particular, we use one-year lagged book assets (AT) as the sorting variable to rank firms by AT for every year over the 1978-2013 period. I assign the firms in the bottom quintile of the annual asset distribution to the constrained group, and those in the remaining to the unconstrained group.

[5] Hadlock and Pierce (2009) categorize a firm's financial constraint status by carefully reading statements made by managers in SEC filings for a sample of randomly selected firms from 1995 to 2004. They find that their proposed index, based on firm size and age, outperforms other approaches commonly used in the literature, e.g., the Kaplan and Zingales index and the Whited and Wu index, which rely on endogenous financial choices, such as cash holdings or leverage.

In the second approach, I use an index constructed by Hadlock and Pierce (2009) as a proxy for the severity of financial constraints, which is referred to as the size-age or SA index. Specifically, they find a nonlinear role of both size and age in predicting the constraint. At certain point, roughly in the sample's ninety-fifth percentile, the relation between the constraint and firm characteristics becomes essentially flat. Below these cutoffs, they uncover a quadratic relation between size and the constraint and a linear relation between age and the constraint. The index is calculated as[6]

$$SA = (-0.737 \cdot Size) + (0.043 \cdot Size^2) - (0.040 \cdot Age).$$

Similar to the first approach, for each of our sample years, I rank firms according to their individual SA index. I then assign firms in the top tercile of the distribution of the SA index to the financially constrained group, and those in the bottom tercile to the financially unconstrained group.

Table 1 illustrates that more financially constrained firms do suffer more from the misallocation due to financial frictions. The output loss within these firms ranges from 5 to 6.7 percent while it is much smaller (2 to 4 percent) within less financially constrained firms. This conclusion holds across other measures of cost of capital.

Since firm's borrowing cost includes both equity and debt cost of financing, a more reasonable cost of capital is firm's weighted average cost of capital (WACC). Given that equity cost of capital is a levered return on capital, it is expected that the dispersion of equity cost of capital can exaggerate the dispersion of firm's actual borrowing cost. My results in Table 1 provide an upper bound of the impact of misallocation due to financial frictions. I also measure firm's WACC given the equity cost of capital and do the same exercises as Table 1, using WACC.

[6] *Size* equals the log of inflation-adjusted book assets with Producer Price Index (PPI) as the deflator, and Age is proxied by the number of years since the firm's first year of observation in Compustat.

Table 2 shows that the TFP losses that can be accounted for due to financial frictions are smaller than those implied in Table 1. They range from 2.5 to 5 percent based on the various measures of equity cost of capital. The measured TFP loss is slightly larger than that in Gilchrist et al. (2013) (from 1.75 to 3.4 percent), and is about the same as Midrigan and Xu (2014) (on the order of 5 percent). However, it is significantly smaller than that in Hsieh and Klenow (2009) (about 30 percent).

Two reasons can lead to the difference between my result and Hsieh and Klenow (2009). First, the timing of the investment matters for the measurement of TFP losses, that can be corrected in reality. In Hsieh and Klenow (2009), firms can observe their productivity shocks before making the investment decision. The magnitude of misallocation is manifested in the dispersion of realized marginal product of capital. In my framework, firms make investment decision before the productivity shock yield. And, the dispersion of firm's marginal cost of financing is mapped into TFP losses due to the misallocation. Second, I try to characterize the TFP losses explicitly arising from the heterogenous borrowing costs; whereas the dispersion of marginal product of capital may involve alternative sources of frictions such as policy-induced tax distortions; fixed production costs; difference between average and marginal products due to adjustment costs.

Finally, I calculate the time series of TFP losses by the two methods using ICC. The first method (the left panel of Figure 1) shows that the TFP losses due to financial friction is at least 5% in both the 2000's dot-com bubble and the recent Great Recession. This suggests that the disruption in finance sector does distort firm's capital allocation and can amplify the output losses. I also calculate TFP losses within the two subsectors of the manufacturing firms and within the two subgroups of different financially constrained firms (Figure 2 and 3). The cyclicality of TFP losses in these groups of firms is similar to that for the overall manufacturing industry. Indeed, the TFP losses within more constrained firms are always greater than those in the less constrained firms.

2.3.1 Impact of Risk Exposure

I address the concern that the equity cost of capital may also contain risk component other than that due to financial constraints; hence, the measured TFP losses may be driven by the firm's differences of risk exposure. The key measure for implied TFP loss is the dispersion of borrowing cost that arises from the financial friction, as in equation (2.7).

I regress the industry returns on the Fama-French 3 factors and proxy firm's borrowing cost due to financial friction by

$$r_{i,t} - (\hat{\beta}^{MKT}_{i,t} - \hat{\beta}^{MKT}) \times \overline{MKT} - (\hat{\beta}^{SMB}_{i,t} - \hat{\beta}^{SMB}) \times \overline{SMB} - (\hat{\beta}^{HML}_{i,t} - \hat{\beta}^{HML}) \times \overline{HML}.$$

First, individual risk exposure is eliminated from firm's equity cost of capital, which is then compensated for the overall cost of capital for the manufacturing industry ($\hat{\beta}^{MKT}$, $\hat{\beta}^{SMB}$ and $\hat{\beta}^{HML}$). Industry risk exposures ($\hat{\beta}^{MKT}_i$, $\hat{\beta}^{SMB}_i$ and $\hat{\beta}^{HML}_i$) are first estimated and then are assigned to those firms that belong to the specific industry i. This measure is employed to execute the exercises of computing TFP losses.

The results are shown in Table 3. The magnitude of TFP losses implied by this measure are aligned with that in Table 1, which suggests that the dispersion in heterogenous borrowing costs is mostly a source of financial frictions.

2.3.2 Comparative statics with respect to parameters

This section studies how the TFP losses would vary with respect to the different sets of parameters. First, I keep α and δ to be the same as those in the benchmark case and let the decreasing return to scale η vary from 1/2, 2/3 to 0.85. The TFP losses would increase together with that in η. When η is approaching 1, the production function of firms is closer to constant return to scale. And, the most productive firm would take all capital in the efficient case whereas the distortion in the capital allocation would induce the greatest loss for the aggregate productivity.

Then, I keep η and δ to be the same as those in the benchmark case and let the labor share parameter α vary from 0, 1/2 to 2/3. The result suggests that the TFP losses would decrease with the increase in α. When capital is the only productive input, the misallocation can lead to about 15 percent of TFP loss. Since the heterogeneity in cost of capital creates the wedge in the marginal product of capital, the larger the share of capital in the production technology would imply a greater impact of misallocation on output losses.

Finally, I keep α and η to be the same as those in the benchmark case and let the depreciation rate δ vary from 0.06, 0.10 to 0.15. The result indicates that the TFP losses would decrease with the increase in δ.

2.3.3 Comparison to Hsieh and Klenow (2009)

As mentioned in the introduction, the methodology proposed by Hsieh and Klenow (2009) implies a huge TFP losses for the U.S. manufacturing sector due to misallocation. In their framework, the TFP losses are manifested in the dispersion in marginal revenue products of capital and labor, though they recognize that plant-based marginal revenue products might contain big measurement error. As shown in equation (2.2), the dispersion of equity cost of capital captures the variation in the expected marginal product of capital. Hence, it is interesting to compare the relative magnitude of the variation in the realized marginal product of capital and in the cost of equity capital.

Table 5 reports the dispersion in the log of the sales-to-capital ratio and in the log of cost of capital as measured by $\log(r_e + \delta)$. In the first column, the log of the sales-to-capital accounts for heterogeneity by removing industry-level (classified by four-digit SICCD) sales-to-capital from the firm specific value. The third column focuses on the dispersion of firm's long-run marginal product of capital by first computing the firm specific mean of marginal product and then computing the standard deviation of these long-run firm averages relative to their industry means. The cost of capital measures are dealt with the same procedures as marginal product.

As shown in the Table 5, the magnitude of dispersion of marginal product is twice or three times that of dispersion in equity cost of capital. Hence, it seems that the dispersion of realized shocks plays a significant role in the dispersion of marginal product of capital. These results imply that Hsieh-Klenow methodology might overstate the TFP losses due to misallocation relative to the borrow-cost method by using equity cost of capital, provided that the misallocation is driven primarily by distortions in financial markets.

Since firm's expected marginal product of capital equals its borrowing cost (equation (2.2) and (2.3)), it is interesting to examine the dispersion in expected marginal product of capital. After running a cross sectional AR(1) model of $\log(MPK)$, I find that the average AR(1) coefficient is 0.9,[7] and the dispersion in $\mathbb{E}_{t-1}[\log(S_{i,t}/K_{i,t-1})]$ is about 0.61, which is still much larger than the dispersion in equity cost of capital. Since differences in average product of capital may reflect differences in production technologies, and other inefficiencies such as taxes or markups, the dispersion in expected average product can serve as an upper bound on the losses from capital misallocation attributable to financial frictions.

[7] Fama and French (2006) show that current profitability is the most powerful predictor of future profitability, which supports my empirical measure of expected marginal product of capital.

2.3.4 Robustness check: misallocation in both manufacturing and service sector

For robustness check, I examine the TFP losses due to financial frictions in the service sector as well. The results are shown in Table 6. The TFP losses are from 4.2 to 12.4 percent in service sector and are generally larger than those in manufacturing sector.

2.4 Conclusion

This paper tries to answer the quantitative question of how much TFP losses can be attributable to the misallocation of productive inputs due to financial friction. The financial friction is manifested as firm's cost of capital being too high so that it cannot afford to acquire sufficient capital. I adopt a TFP accounting framework to capture such misallocation. Using several measures of equity cost of capital, I show that for a sample of U.S. manufacturing firms, the productivity loss due to financial friction ranges from 3.2% to 6.4%. Overall, these results are similar to Gilchrist et al. (2013), which show that TFP loss is around 1.75% by using interest rate of corporate bond as firm's borrowing cost. TFP losses due to financial friction are relatively modest.

My empirical exercises suggest that the financial market is well-functioned to distribute production resources to their most productive use. However, the time-series calculation of TFP losses show that the recent two recessions did reduce TFP by more than 5%. So, it will be interesting to understand further the evolution of misallocation. Moll (2014) develops a dynamic general equilibrium model and study the effect of firm's collateral constraint on capital misallocation and aggregate productivity. Moll (2014) argues that the misallocation can be small in the steady state since the entrepreneurs can save out of the financing constraint. In my future work, a dynamic model can be studied to guide the measurement of the accumulation of TFP losses over time.

Table 2.1: TFP losses due to resource misallocation

	$\bar{r}$	σ_r	r_{10}	r_{90}	σ_{w_l}	σ_{w_k}	TFP Loss 1	TFP Loss 2
Panel 1: Cost of Equity Capital by ICC								
All	12.61	4.46	8.18	17.82	0.61	0.80	3.22	4.12
Durb	12.51	4.47	8.11	17.66	0.61	0.80	3.24	4.01
NonD	13.24	4.35	8.59	19.06	0.59	0.77	3.03	4.65
Small	14.13	6.09	7.52	21.85	0.79	1.02	5.32	6.42
Large	12.23	3.85	8.27	16.90	0.55	0.72	2.62	4.09
Most	13.58	5.73	7.33	20.73	0.76	0.98	4.90	6.73
Least	11.90	3.27	8.53	16.06	0.47	0.62	1.93	3.96
Panel 2: Cost of Equity Capital by CAPM model								
All	16.08	5.81	9.08	23.34	0.76	0.99	5.01	5.92
Durb	16.32	5.84	9.40	23.62	0.76	0.99	4.98	5.66
NonD	14.55	5.34	8.12	21.49	0.75	0.98	4.85	6.82
Small	15.86	6.83	7.45	24.67	0.91	1.19	7.18	8.65
Large	16.24	5.62	9.60	23.35	0.73	0.95	4.59	5.91
Most	16.26	6.76	7.87	25.04	0.89	1.16	6.79	8.74
Least	15.39	4.68	9.67	21.19	0.62	0.81	3.32	5.63
Panel 3: Cost of Equity Capital by FF3 model								
All	18.08	7.36	9.99	27.03	0.87	1.12	6.41	6.44
Durb	18.23	7.36	10.10	27.22	0.87	1.12	6.37	6.38
NonD	17.16	7.25	9.25	25.80	0.88	1.14	6.58	6.23
Small	18.42	9.12	8.01	30.67	1.09	1.40	10.01	11.52
Large	17.90	6.90	10.27	26.50	0.82	1.06	5.67	6.42
Most	18.60	8.87	8.42	30.47	1.05	1.35	9.25	11.29
Least	17.22	5.41	11.05	23.92	0.65	0.84	3.60	6.05

The table shows the implied TFP loss due to the misallocation that is attributable to financial frictions. The equity cost of capital is estimated by ICC, CAPM, and FF3 factor model respectively. The mean, standard deviation, 10th and 90th percentile of cost of capital is in percent. The implied TFP losses are also in percent. "TFP loss 1" is the implied TFP loss that is calculated by the dispersion in the firm-specific equity cost of capital using the log-normal approximation. "TFP loss 2" is the implied TFP loss that uses both the equity cost of capital and the sale. Sample period: 1978 to 2013. For ICC: No. of firms = 4628; Obs. = 44066. For CAPM and FF3: No. of firms = 6065; Obs. = 65431.

Table 2.2: TFP losses due to resource misallocation using WACC

	$\bar{r}$	σ_r	r_{10}	r_{90}	σ_{w_l}	σ_{w_k}	TFP Loss 1	TFP Loss 2
Panel 1: WACC using r_{ICC}								
All	11.32	3.71	7.74	15.59	0.53	0.70	2.46	2.97
Durb	11.30	3.77	7.71	15.55	0.54	0.71	2.53	2.92
NonD	11.43	3.30	7.90	15.75	0.49	0.64	2.07	3.22
Small	12.36	4.77	7.14	17.97	0.67	0.88	3.88	5.01
Large	10.73	2.95	7.71	14.36	0.45	0.60	1.79	2.92
Most	12.04	4.35	7.43	17.04	0.62	0.81	3.33	4.39
Least	10.03	2.43	7.62	12.66	0.37	0.49	1.21	2.70
Panel 2: WACC using r_{CAPM}								
All	14.25	5.10	8.33	20.90	0.70	0.91	4.20	4.80
Durb	14.54	5.17	8.49	21.29	0.70	0.91	4.23	4.64
NonD	12.41	4.21	7.22	18.00	0.62	0.82	3.42	5.06
Small	14.54	6.11	7.18	22.34	0.84	1.10	6.08	7.31
Large	14.24	4.95	8.56	20.63	0.67	0.88	3.90	4.80
Most	14.79	6.02	7.45	22.64	0.82	1.07	5.75	7.47
Least	13.19	3.93	8.33	18.22	0.56	0.73	2.68	4.57
Panel 3: WACC using r_{FF3}								
All	15.79	6.19	9.15	23.21	0.77	1.00	5.06	4.84
Durb	16.03	6.27	9.30	23.55	0.78	1.00	5.12	4.82
NonD	14.27	5.41	8.24	20.76	0.71	0.93	4.36	4.24
Small	16.67	7.95	7.65	26.79	0.98	1.27	8.18	9.26
Large	15.43	5.68	9.28	22.34	0.72	0.93	4.38	4.83
Most	16.70	7.69	7.87	26.77	0.95	1.22	7.58	9.33
Least	14.42	4.04	9.80	19.26	0.54	0.70	2.45	4.50

The table uses weighted average cost of capital (WACC) and computes the implied TFP loss due to the misallocation that is attributable to financial frictions. The equity cost of capital is proxied by ICC, CAPM, and FF3 factor model respectively. The debt cost of capital is the average cost of debt, which is Item XINT / (Item DLTT + Item DLC). The meaning of each column is the same as those in table 1.

Table 2.3: TFP losses due to resource misallocation controlling for risk

	$\bar{r}$	σ_r	r_{10}	r_{90}	σ_{w_l}	σ_{w_k}	TFP Loss 1	TFP Loss 2
Panel 1: ICC (Remove Risk Component)								
All	13.40	4.65	8.19	19.05	0.63	0.82	3.43	4.79
Durb	13.37	4.60	8.29	18.97	0.62	0.81	3.32	4.74
NonD	13.56	4.96	7.67	20.11	0.69	0.90	4.11	4.56
Small	14.73	5.37	8.63	21.69	0.70	0.92	4.25	6.12
Large	12.64	4.15	7.92	17.72	0.59	0.77	3.00	4.75
Most	14.34	5.08	8.50	20.64	0.67	0.88	3.90	5.71
Least	11.55	3.71	7.45	16.24	0.54	0.72	2.59	4.55
Panel 2: WACC (Remove Risk Component)								
All	10.64	3.85	6.42	15.35	0.58	0.77	3.00	3.59
Durb	10.42	3.88	6.26	15.09	0.59	0.78	3.07	3.65
NonD	12.06	3.34	8.32	16.59	0.48	0.63	2.02	2.88
Small	11.57	4.77	6.28	17.66	0.71	0.93	4.37	5.64
Large	10.07	3.28	6.26	14.01	0.52	0.70	2.43	3.56
Most	11.23	4.41	6.31	16.73	0.66	0.87	3.83	5.02
Least	9.56	2.92	6.17	13.08	0.47	0.63	1.97	3.47

The table shows the implied TFP loss due to the misallocation that is attributable to financial frictions.
The risk exposure to the Fama-French 3 factors is eliminated from the ICC and WACC. The meaning of each column is the same as that in table 1.

Table 2.4: Comparative Statics with respect to Parameters

η	$\alpha = 2/3$ $\delta = 0.06$	α	$\eta = 0.85$ $\delta = 0.06$	δ	$\alpha = 2/3$ $\eta = 0.85$
1/2	0.71	0	14.55	0.06	3.22
2/3	1.28	1/2	5.34	0.10	2.37
0.85	3.22	2/3	3.22	0.15	1.77

The table computes the implied TFP loss (in percent) given different sets of parameters, using the first approximation method. The equity cost of capital is estimated by ICC.
The first set of parameters: $\alpha = 2/3$ and $\delta = 0.06$ while $\eta = 0.5, 2/3$, and 0.85.
The second set of parameters: $\eta = 0.85$ and $\delta = 0.06$ while $\alpha = 0, 0.5$ and $2/3$.
The third set of parameters: $\alpha = 2/3$ and $\eta = 0.85$ while $\delta = 0.06, 0.1$ and 0.15.

Table 2.5: Dispersion in $\log(MPK)$ and in $\log(r_e + \delta)$

	std 1	Ratio b/w the two disp.	std 2	Ratio b/w the two disp.
$\log(S_{i,t}/K_{i,t-1})$	0.721		0.696	
$\log(r_{ICC} + \delta)$	0.263	2.74	0.225	3.09
$\log(r_{CAPM} + \delta)$	0.307	2.35	0.253	2.75
$\log(r_{FF3} + \delta)$	0.336	2.15	0.302	2.31

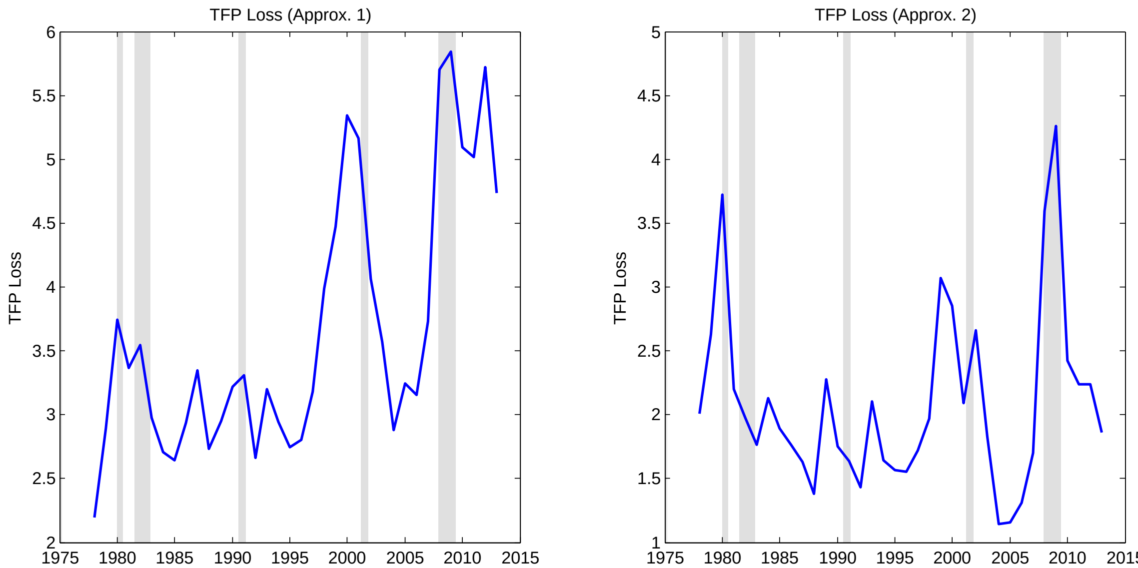
The table compares the dispersion of the marginal product of capital and the equity cost of capital. The calculation of the first standard deviation uses industry-adjusted (based on four-digit SICCD code) measures of both $\log(S_{i,t}/K_{i,t-1})$ and $\log(r_e+\delta)$. The calculation of the second standard deviation takes the sample average of these measures for each firm, and then removes industry-fixed levels. The depreciation rate $\delta = 0.06$ for all cases.

Table 2.6: TFP losses due to resource misallocation using service industry

	$\bar{r}$	σ_r	r_{10}	r_{90}	σ_{w_l}	σ_{w_k}	TFP Loss 1	TFP Loss 2
Panel 1: Cost of Equity Capital by ICC								
Manu	12.61	4.46	8.18	17.82	0.61	0.80	3.22	4.12
Service	11.57	5.06	6.74	16.92	0.70	0.92	4.25	5.17
Manu & SV	12.18	4.93	7.24	17.64	0.68	0.89	3.99	4.94
Panel 2: Cost of Equity Capital by CAPM								
Manu	16.08	5.81	9.08	23.34	0.76	0.99	5.01	5.92
Service	15.65	6.98	7.69	24.86	0.93	1.21	7.46	7.19
Manu & SV	15.79	6.39	8.25	23.86	0.86	1.12	6.37	6.48
Panel 3: Cost of Equity Capital by FF3								
Manu	18.08	7.36	9.99	27.03	0.87	1.12	6.41	6.44
Service	16.75	9.09	6.28	28.38	1.20	1.57	12.44	8.22
Manu & SV	17.06	8.44	7.49	27.27	1.11	1.45	10.62	7.42

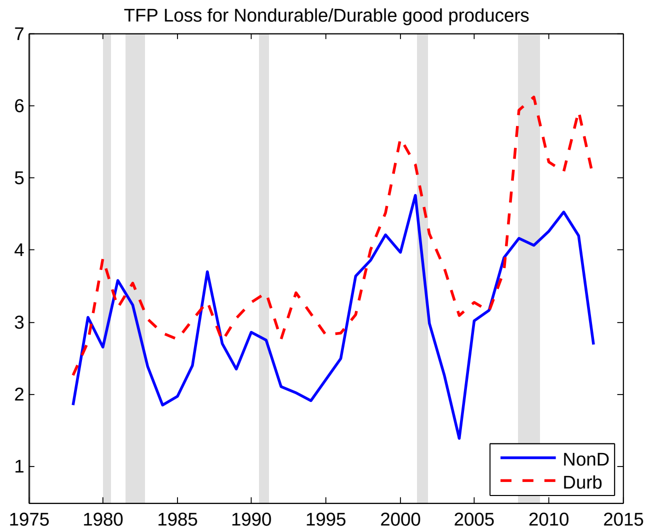
The table shows the implied TFP loss within the manufacturing, service industry separately and for the two industries altogether. The equity cost of capital is estimated by ICC, CAPM, and FF3 factor model respectively. The meaning of each column is the same as those in table 1.

Figure 2.1: Time Series of Implied TFP Losses



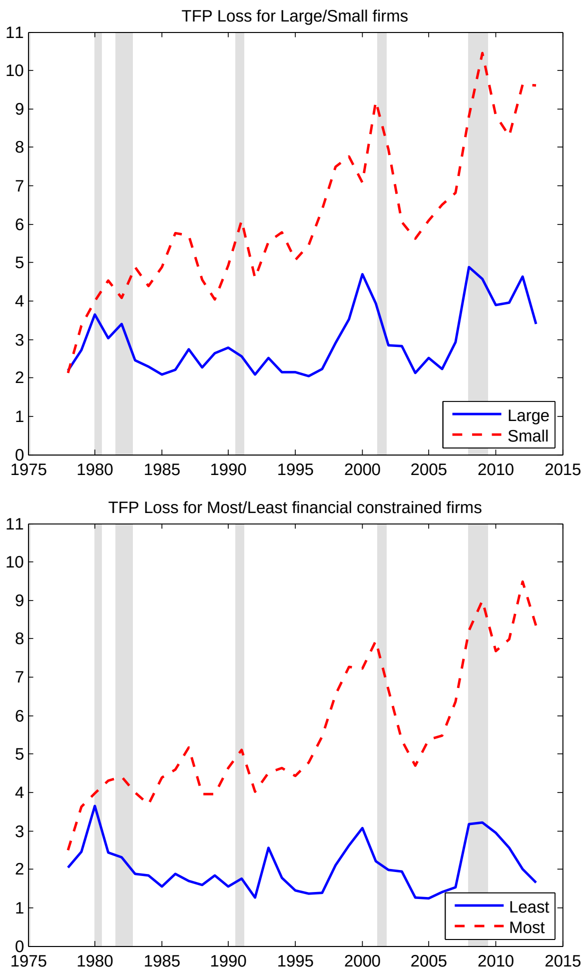
The left panel and right panel plot the time series of the implied TFP loss by method 1 and 2 respectively. Equity cost of capital is measured by ICC. The shaded vertical bars represent the NBER-dated recessions.

Figure 2.2: TFP Losses within the manufacturing subsectors



The plot shows the time series of the implied TFP losses in the durable goods and non-durable goods producers respectively. Equity cost of capital is measured by ICC. The shaded vertical bars represent the NBER-dated recessions.

Figure 2.3: TFP Losses within the different financially constrained firms



The top panel plots the time-series of the TFP losses (method 1) in large and small firms. The bottom panel plots the time-series of the TFP losses in the most and the least financially constrained firms. Equity cost of capital is measured by ICC.

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Appendices

I follow Pástor et al. (2008) closely to compute the ICC. In order to compute ICC, I will need to impute firm's future cash flows:

$$E_t(FCFE_{t+k}) = FE_{t+k} \times (1 - b_{t+k}),$$

where FE_{t+k} and b_{t+k} are the forecasts of earnings and the plowback rate for year $t+k$. The plowback rate is the fraction of earnings that is reinvested in the firm, or one minus the payout ratio. The earning forecasts from year $t+1$ to $t+3$ are based on analysts, and the forecasts from year $t+4$ to $t+T+1$ are computed by mean-reverting the year $t+3$ earnings growth rate to its steady-state value by year $t+T+2$.

I impose an exponential rate of decline to mean-revert the year $t+3$ growth rate to the steady-state growth rate. Specifically, I compute earnings growth rates and earnings forecasts for years $t+4$ to $t+T+1$ ($k = 4, \ldots, T+1$) as follows:

$$g_{t+k} = g_{t+k-1} \times \exp[\log(g/g_{t+3})/(T-1)],$$
$$FE_{t+k} = FE_{t+k-1} \times (1 + g_{t+k}).$$

I forecast plowback rates in two stages: (1) explicitly forecast plowback rates for years $t+1$ and $t+2$ using Compustat data, and (2) mean-revert the plowback rates between years $t+2$ and $t+T+1$ linearly to a steady-state value computed from the sustainable growth rate formula. This formula assumes that, in the steady-state, the product of steady-state return on new investments (ROI) and the steady-state plowback rate is equal to the steady-state growth rate in earnings; that is $g = ROI \times b$. Thus, our main assumptions are that the earnings growth rate reverts to the long-run nominal GDP growth rate, and that the return on new investment, ROI, reverts to the (implied) cost of equity, r_e.

Substituting $ROI = r_e$ in the sustainable growth rate formula and solving for b provides the steady-state value for the plowback rate, $b = g/r_e$. The intermediate plowback rates from $t+3$ to $t+T$ $(k = 3, \ldots, T)$ are computed as follows:

$$b_{t+k} = b_{t+k-1} - \frac{b_{t+2} - b}{T-1}.$$

The terminal value at time $t+T$, TV_{t+T} is computed as the present value of a perpetuity equal to the ratio of the year $t+T+1$ earnings forecast divided by the cost of equity:

$$TV_{t+T} = \frac{FE_{t+T+1}}{r_e},$$

where FE_{t+T+1} is the earnings forecast for year $t+T+1$. Note that the use of the no-growth perpetuity formula does not imply that earnings or cash flows do not grow after period $t+T$. Rather, it simply implies that any new investments after year $t+T$ earn zero economic profits. In other words, any growth in earnings or cash flow after year T is value irrelevant.

I solve the implied cost of capital(ICC) from the following tractable finite-horizon model:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k}(1-b_{t+k})}{(1+r_e)^k} + \frac{FE_{t+T+1}}{r_e(1+r_e)^T}.$$

I use a 15-year horizon ($T = 15$), as in Pástor et al. (2008).

Next, I describe the estimate of equity cost of capital by the factor pricing model. To estimate the factor loadings, for each stock i in year t (between 1978 and 2013), I run the following time-series regression using monthly data from year $t-4$ to t (I require a minimum of 24 months of data as in Fama and French (1992)):

$$r_i - r_f = \alpha_i + \beta_i^{MPK}(r_M - r_f) + \beta_i^{HML} HML + \beta_i^{SMB} SMB + \epsilon_i,$$

where $(r_i - r_f)$ is the monthly excess return of stock i, $r_M - r_f$ is the excess return of the market portfolio, HML and SMB are the "high-minus-low" and "small-minus-large" factor respectively. I then construct the Fama-French three factor cost of equity capital of firm i in year t as follows:

$$r_{i,FF3} = r_f + \hat{\beta}_{i,t}^{MKT}(\overline{r_M - r_f}) + \hat{\beta}_{i,t}^{HML}\overline{HML} + \hat{\beta}_{i,t}^{SMB}\overline{SMB}$$

where $\overline{r_M - r_f}$, $\overline{HML}$ and $\overline{SMB}$ are the average annualized returns of the Fama-French (1993) factors calculated over the period 1978-2013, and the $\hat{\beta}$'s are the ordinary least squares (OLS) estimates from the previous regression.

Finally, I describe how to measure weighted average cost of capital (WACC), which is defined as

$$r_{WACC} = \frac{E}{V} r_E + \frac{D}{V} r_D (1 - \tau_c).$$

Computation of r_{WACC} requires measuring r_e, r_D, leverage $\frac{D}{V}$ and tax rate τ_c. For equity cost of capital, I use the three measures r_{ICC}, r_{CAPM}, and r_{FF3}. For debt cost of capital, I use the interest expenses on firm's total debt: Compustat item XINT/(DLTT + DLC). Firm's market leverage is given as firm's total debt over its market value of total asset: Compustat item $(DLTT+DLC)/(AT+PRCC_F*CSHO-SEQ-TXDB)$.