ESSAYS ON CORPORATE INVESTMENT

A THESIS
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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June, 2013

Acknowledgements

I am deeply indebted to my advisor Professor Murray Frank for his invaluable guidance and generous support from the beginning till the end of my graduate studies at the Finance department. I am also especially grateful to my committee members Professor Philip Bond and Professor Raj Singh (Chair) for their insightful comments, continuous encouragement, and tremendous patience. I am also grateful to my committee member Professor Erzo G.J. Luttmer for his kind support. I would never be able to complete my Ph.D. degree without them. Finally, many thanks to the faculty, fellow students, and alumni of the Carlson School of Management. I benefit a lot from the discussions with them.

Dedication

Dedicated to my parents and my wife, for their unconditional love, care, and sacrifice.

Abstract

My dissertation focuses on corporate investment, especially on its connection with asset prices.

The first chapter explores the connection between firms investment and their bond prices, from the perspective of Q theory. The Q theory says that the market-to-book ratio, or the Tobin's Q, contains the information about firm investment opportunities. In this paper, I ask the question whether credit spreads could signal firm investment opportunities just like Tobin's Q. Since both credit spreads and Tobin's Q are market prices, they should contain similar information about the firm. To formally examine this idea, I develop a continuous-time investment model in which an analytical relation is established between the unobservable investment opportunities (marginal Q) and the observable credit spreads. Using U.S. firm level data from 1980 to 2011, I find that credit spreads are a statistically important predictor of firm investment and their explanatory power is higher than that of Tobin's Q. The empirical evidence shows that credit spreads pick up the effects of financial frictions (costly external financing and debt overhang), which drive a wedge between marginal and Tobin's Q. This explains why credit spreads are a better proxy for marginal Q. Consistent with the model, the credit spread elasticity of investment is associated with firm and bond characteristics.

The second chapter is coauthored with Murray Frank, and it is a study of the impact of the cost of capital on corporate investment. Empirically, high leverage and high cost of debt reduce investment. According to standard theory, high cost of equity has a negative effect on investment. When well known models such as the CAPM or the Fama and French model are used to infer the cost of equity, the cost of equity has a positive effect on investment. When factor augmented vector autoregressive (FAVAR) approach is used to allow for a much wider range of determinants, the anomalous result persists. However, when an implied cost of equity capital approach is used, the theoretically predicted negative sign is observed.

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Chapter 1

Credit Spreads and Investment Opportunities

1.1 Introduction

Determining how firms make investment decisions lies at the heart of corporate finance. The leading theory is the Q theory of investment, which says that subject to capital adjustment costs, investment decisions are driven by investment opportunities (marginal Q). Although its intuition is simple and appealing, attempts to test Q theory have met with mixed success. The explanatory power of Tobin's Q in an investment regression is low.[1] One obvious problem when testing the theory is that the theory relates the optimal investment to marginal Q, which is not

[1] Perhaps the most prominent example of the empirical failure of Q theory is the investment cash-flow sensitivity. Since the seminal work of Fazzari et al. (1988) and summarized by Hubbard (1998), a lot of empirical papers show that investment responds strongly to movements in internal funds (proxied by cash flow) even after one controls for Tobin's Q. However, the recent literature (e.g. Kaplan and Zingales (1997), Erickson and Whited (2000), Gomes (2001), and Alti (2003)) finds that cash-flow sensitivity may not be direct evidence for the failure of Q theory, and its effects diminish over time (Chen and Chen (2011)).

directly observable, and the usual proxy of average Q – the market-to-book ratio, also known as "Tobin's Q" – may badly mis-measure marginal Q (e.g. Erickson and Whited (2000)).

In this paper I propose an alternative approach to testing Q theory. The approach builds on the old insight of Merton (1974) that debt is a derivative claim on a firm's asset value, and hence contains information about future asset values or investment opportunities. I construct a continuous time model of investment, in which the marginal Q is analytically linked to the credit spreads. Theoretically, the observable credit spreads are an alternative proxy for the unobservable marginal Q.

Using U.S. firm level data of credit spreads and investment from 1980 to 2011, I find that credit spreads are a robust and statistically important predictor of firm investment. Importantly, the explanatory power of credit spreads is greater than that of Tobin's Q. In other words, credit spreads really do seem to provide a better proxy for marginal Q than the widely used Tobin's Q. This is the first firm level evidence, and is consistent with the aggregate evidence in Philippon (2009).

Moreover, I explore four possible reasons for the better performance of credit spreads, and find that it seems due to the effects of financial frictions. Hennessy et al. (2007) show that financial frictions drive a wedge between marginal and Tobin's Q. While marginal Q is still a sufficient statistic for investment, Tobin's Q is not. Empirically, credit spreads capture this wedge of financial frictions.

Particularly, I examine two financial frictions in Hennessy et al. (2007): costly external financing and debt overhang. First, I find that credit spreads have a stronger correlation with both financial frictions than Tobin's Q. Proxied by several popular financial constraint indices (e.g. Hennessy et al. (2007)), the variation in the effects of costly external financing explains as much as 27% of the variation in credit spreads. This number for Tobin's Q is at most 2%. Debt overhang term is usually computed using default probabilities and book leverage (e.g. Alanis and Chava (2012)), both of which are naturally more connected to credit spreads than Tobin's Q.

Second, among those two frictions, the effect of debt overhang is the key force. For firms with less debt overhang (namely, low leverage and low default probability), the explanatory power of credit spreads is close to that of Tobin's Q. For firms with more debt overhang, the explanatory power of credit spreads increases nearly 70%, while it barely changes for Tobin's Q. The impact of costly external financing is tiny, because the firms in the dataset being studied have public debt, making them precisely the ones that have easy access to the capital market.

Philippon (2009) proposes that equity mispricing may be the reason for the better performance of his bond price based measure in explaining aggregate investment. However, I do not find evidence that bond market prices are less noisy than stock market prices. Following the approach in Stambaugh et al. (2012), I find that both markets seem to have a potential mispricing problem. Consistently, the effects of credit spreads and Tobin's Q do not subsume each other in regressions. This suggests that neither is a perfect proxy for marginal Q and that measurement error exists in both of them.

Last but not least, in the model the elasticity[2] of investment with respect to credit spreads is connected to both firm characteristics and bond characteristics. Consistent with the model, empirically the investment elasticity is high both for firms with low sales growth and for firms with high stock return volatility. The credit spreads of long term bonds have higher elasticities than do short term bonds. In contrast, existing investment models (e.g. Abel and Eberly (1994)) usually link

[2]The word "elasticity" here does not imply there is a causality between credit spreads and investment. It merely measures the co-movement.

investment-Q sensitivity to unobservable firm capital adjustment costs, making it impossible to generate cross sectional predictions of coefficients on the proxy for marginal Q in investment regressions. These predictions are an additional channel to test Q theory, and this paper finds supporting evidence for them.

This paper belongs to the literature of neo-classical investment (Q theory), which has a long tradition. A recent survey is provided by Bond and Van Reenen (2007). Here, I focus on several recent papers that examine the credit market and investment. The most closely related paper is by Philippon (2009). He numerically solves a similar model and shows that there is a one to one mapping between bond prices and Q. He finds that the bond price implied Q performs much better than the traditional measure. My paper has three basic differences from Philippon (2009). First, Philippon's study focuses on aggregate data. This paper studies firm level data. Second, Philippon solves the model numerically. I have an analytical solution, which provides two benefits: (1) it shows that the credit spread itself is a proxy for marginal Q, and it largely facilitates the empirical implementation; (2) it reveals the relation between firm/bond characteristics and elasticity of investment with respect to credit spreads. Third, I provide empirical evidence to explain the better performance of credit spreads. Due to data limitations at the aggregate level, Philippon (2009) proposes two theories without any supporting evidence.

Gilchrist and Zakrajsek (2007) study the empirical effect of cost of capital on investment. They use credit spreads as a proxy for financing costs. I take a different view of credit spreads and offer an alternative model. Particularly, this paper finds that firms that have access to public debt markets are unlikely to be financially constrained.

This paper is also related to the recent macro-finance literature that studies the connection between financial market and macroeconomics (e.g. Miao and Wang

(2010), Gomes and Schmid (2010), and Gilchrist et al. (2010)). All of these papers focus on the theory, and they calibrate dynamic general equilibrium models with a financial market. They find that credit spreads are linked to corporate bond prices, which affect investment through Tobin's Q. This paper shares a similar theoretical insight but instead focuses on the firm level empirical evidence.

This paper is more loosely connected to the literature on measurement errors in Q. Eberly et al. (2009) specify a measurement error process for Tobin's Q and find the "contaminated" Tobin's Q fits the data well. Erickson and Whited (2000) use measurement error–consistent generalized method of moments estimators and improve the performance of Tobin's Q. The effect of measurement error for credit spreads may merit future study.

This paper is organized as follows. Section 1.2 introduces the model. Section 1.3 discusses the data source, variable construction, and summary statistics. Section 1.4 provides empirical analysis and robustness checks. Section 1.5 discusses possible explanations for the better performance of credit spreads. Section 1.6 concludes.

1.2 Model

The marginal Q is the discounted future marginal productivity of one additional unit of capital, and it reflects the future profitability of the firm. The stronger the future profitability, the higher the Q. The bond price, or credit spread, might work in a similar way. Holding other factors constant, a stronger future profitability implies a lower chance of default, resulting in a smaller credit spread or a higher bond price.[3] If a model implies a significant and positive relation between investment and marginal Q, it should also imply a significant and negative relation between investment and credit spreads.

To formalize this idea and motivate the specification in empirical testing, I construct an infinite-period dynamic investment model. The real side of the firm problem is standard. There is one representative firm. At the beginning of each period t, the firm has capital stock K_t, inherited from the end of last period t-1. Also, at the beginning of period t, a shock (combination of aggregate and idiosyncratic shock) hits the firm. The firm then generates cash flow, which is a function of both shock and capital stock. Because capital stock depreciates each period, the firm has to choose how much to invest. Investment incurs adjustment costs. The optimal investment depends on the adjustment costs and the expectation for next period's shock. At the end of period t, the capital stock for next period K_{t+1} is chosen.

On the financing side of the firm, following Philippon (2009), I assume an environment of no tax and no bankruptcy costs. By the Modigliani-Miller theorem, the capital structure is irrelevant here, so we can calculate total firm value and derive investment decisions without knowing the details of debt policy. Tax and bankruptcy costs are crucial for deriving optimal capital structure. However, optimal capital structure is not the focus of this model.

Debt policy does not affect firm value or investment policy, but it does affect credit spreads, which signal the investment opportunities. In the model, the firm keeps issuing and retiring long-term coupon bonds. Unlike asset pricing models

[3] Welch (2004) shows that "U.S. corporations do little to counteract the influence of stock price changes on their capital structures. As a consequence, their debt-equity ratios vary closely with fluctuations in their own stock prices". This is the empirical support for the statement "holding other factors constant". If firms adjust their capital structures actively to absorb shocks, credit spreads may contain little information.

(e.g. Leland (1998), and Goldstein et al. (2001)), the capital structure in this model is not endogenous, as there is no trade off between the bankruptcy costs and tax benefits. Instead, the debt policy needs to be exogenously specified. Here, I assume a debt policy in which the firm keeps a fixed book leverage over time. Therefore, in each period t, the firm issues and retires debt such that at the end of period t, the face value of debt is always proportional to capital stock. This assumption of fixed book leverage ratio is closely related to the asset pricing models, and has been made in similar studies (e.g. Philippon (2009), and Ozdagli (2012)). For example, the EBIT-generating machine in Goldstein et al. (2001) could be thought as the capital stock which has a fixed size and does not depreciate overtime. The optimal capital structure is obtained when the equity holders maximize their value by choosing an optimal coupon rate of a perpetual debt. It is equivalent to fix the book value of debt. Therefore, the optimal capital structure is essentially a fixed book leverage ratio. Figure 1.1 illustrates book leverage ratio for 10 market-to-book portfolios for all industrial COMPUSTAT firms from 1965 to 2011. The figure shows there is not much variation and book leverage is indeed flat across different portfolios. Using a different definition of book leverage, Ozdagli (2012) finds a similar result.

Now, the financing side of firm is much clearer. At the beginning of period t, the real production generates cash flow. Then, the firm chooses how much to invest independent of its financing. After making its investment decision, the firm issues new debt and retires a certain portion of old debt such that the total face value of debt is proportional to the end of period capital stock. If the sum of cash flow and net proceeds from debt (new issuance - interest payment - retirement) is high enough to finance the optimal investment, the remaining cash flow goes to the equity holders (positive dividend). If the sum is insufficient, the equity holders finance the firm (negative dividend). If the equity holders' continuation value is below zero, the debt holders take over the firm.

With these assumptions, I construct a continuous time model for tractability. Because financing does not affect the real side of the firm, we can solve investment and firm value first. Total firm value is given by:

$$V_t = V(K_t, a_t) = \max_{I_s} E_t \int_t^{\infty} [h a_s^{\theta} K_s - c(I_s)] e^{-r(s-t)} ds \tag{1.1}$$

s.t. $dK_t = (I_t - \delta K_t)dt$ and $da_t = a_t \mu dt + a_t \sigma dW_t$, where the K_t is the capital stock, I_t is the investment, a_t is the shock, $c(I_t)$ is the adjustment cost function, and δ is the depreciation rate. The shock a_t is exogenous and governed by a geometric Brownian motion with drift $\mu > 0$ and volatility $\sigma > 0$, both of which are constant. The firm optimally chooses its investment level every period given the motion of capital and shock.

The total sale is $h a_s^{\theta} K_s$. It can be shown that it is from a constant return of scale Cobb-Douglas production function with two-factor inputs: labor and capital. If the capital share is α and labor wage w is fixed, $h a_s^{\theta} K_s$ is the optimized output over the labor input with $h = (1-\alpha)(\alpha/w)^{\alpha/(1-\alpha)}$ and $\theta = 1/(1-\alpha)$.

Following Abel (1983), Abel and Eberly (1994) and Abel and Eberly (1997), I assume the adjustment cost $c(I) = \beta I + \gamma I^{n/(n-1)}$ with $\beta \geq 0$, $\gamma > 0$, and $n = \{2, 4, 6...\}$. Because $c(I)$ is independent of the capital stock, K_t, the firm value is characterized by the following equation:[4]

$$V(K_t, a_t) = q(a_t) K_t + J(a_t) \tag{1.2}$$

[4] See Abel and Eberly (1997) for details

with marginal Q,

$$q(a_t) = \frac{ha_t^\theta}{r + \delta - \theta\mu - \frac{1}{2}\theta(\theta - 1)\sigma^2} \tag{1.3}$$

, $J(a_t) = \frac{[q(a_t)-\beta]^n (n-1)^{n-1} n^{-n} \gamma^{(1-n)}}{r-\theta\mu-\frac{1}{2}\theta(\theta-1)\sigma^2}$, and $r - \theta\mu - \frac{1}{2}\theta(\theta - 1)\sigma^2 > 0$. The optimal investment is a function of the marginal Q:

$$I = \left(\frac{n-1}{n\gamma}\right)^{n-1} [q(a_t) - \beta]^{n-1}\,. \tag{1.4}$$

If we take the natural logarithm on both sides and a linear first order approximation around $\beta = 0$, we have $log(I) \approx log\left(\frac{n-1}{n\gamma}\right)^{n-1} + (n-1)log\,[q(a_t)]$.

Because we know $q(a_t)$ and $J(a_t)$, we can pin down the firm value V_t, which is independent of capital structure. In this setting, the marginal Q, which is $q(a_t)$, is not the same as the average Q, which is $q(a_t) + \frac{J(a_t)}{K_t}$. The difference is time varying and depends on both the capital stock and shock level. The $J(a_t) \geqslant 0$, and it is the "firm rents" accruing to the adjustment technology which is a scarce resource.

The debt structure follows Leland (1998) and Hackbarth et al. (2006). The face value per unit of bond is normalized to 1, that is, p=1, and the coupon is c. The book leverage ratio is fixed at ψ, and total units of debt outstanding are ψK_t. The firm retires m fraction principle each period. In each period, the total principle retired is $m\psi K_t$, and the total coupon is $c\psi K_t$. The per unit bond price does not depend on K_t and satisfies the following ordinary differential equation (ODE) before default:

$$c + m - (r + m)b(a_t) + \mu a_t b'(a_t) + \frac{1}{2}\sigma^2 a_t^2 b''(a_t) = 0. \tag{1.5}$$

To solve this model, we start by guessing the solution to the ODE:

$$b(a) = A_+ a^{\gamma_+} + A_- a^{\gamma_-} + \frac{c+m}{r+m} \tag{1.6}$$

with $\gamma_+ = 0.5 - \frac{\mu}{\sigma^2} + \sqrt{(0.5 - \frac{\mu}{\sigma^2})^2 + \frac{2(r+m)}{\sigma^2}}$ and $\gamma_- = 0.5 - \frac{\mu}{\sigma^2} - \sqrt{(0.5 - \frac{\mu}{\sigma^2})^2 + \frac{2(r+m)}{\sigma^2}}$.

We need two boundary conditions to pin down A_+ and A_-. As $a_t \to \infty$, there is no default. Therefore, we have $b(a_t) = \frac{c+m}{r+m}$ and $A_+ = 0$. As a_t hits lower bound $\underline{a}$, the bond holders take over the firm and we have $\psi b(\underline{a}) K_t = q(\underline{a}) K_t + J(\underline{a})$. A_- is independent of K_t, so we have $J(\underline{a}) = 0$. It follows that $q(\underline{a}) = \beta$, and the $\underline{a} = \{\frac{[r+\delta-\theta\mu-\frac{1}{2}\theta(\theta-1)\sigma^2]\beta}{h}\}^{\frac{1}{\theta}}$. Since $\underline{a}$ is known, from $\psi b(\underline{a}) = \beta$, we have $A_- = \frac{(\frac{\beta}{\psi} - \frac{c+m}{r+m}) h^{\frac{\gamma_-}{\theta}}}{\{[r+\delta-\theta\mu-\frac{1}{2}\theta(\theta-1)\sigma^2]\beta\}^{\frac{\gamma_-}{\theta}}}$.

Now, we identify all the parameters in the solution. The bond yields y are defined as:

$$y(a_t) = \frac{c+m}{b(a_t)} - m. \tag{1.7}$$

The marginal Q can be expressed in terms of bond price b:

$$q(b) = (\frac{c+m}{r+m} - \frac{\beta}{\psi})^{-\frac{\theta}{\gamma_-}} \beta (\frac{c+m}{r+m} - b)^{\frac{\theta}{\gamma_-}}. \tag{1.8}$$

In the upper panel of Table 1.4 (see later), I provide two plots to show some of the properties of the model. The plot on the left shows the relation between credit spreads and investment as book leverage changes. First, there is a negative monotone relationship between investment and credit spread. Credit spreads do not affect investment directly. Instead, it simply reflects the shock that determines the optimal investment. When the shock is high (low), the marginal Q is high (low), credit spreads are low (high), and investment is high (low). This negative relationship has nothing to do with the financing costs, as real investment decisions are independent of financing decisions in the model. Second, for the same level of credit spreads, a high book leverage firm has a higher investment. The intuition is that for a given level of shock, a more levered firm will have a higher default risk. Credit spreads measure this default risk in model. If the credit spreads of a more levered firm are the same as those of a less levered firm, it must be that the more levered firm receives a better shock, which offsets the leverage effect. A better shock leads to higher marginal Q and higher investment.

The plot on right in Table 1.4 presents the relationship between credit spreads and investment as volatility changes. Volatility works like the leverage in the model, and it affects default risk. For the same level of credit spread, a more volatile firm will invest more. The intuition is the same as book leverage.

For empirical tests, an analytical solution is important. There are two ways to use it. First, we can calibrate the model and employ mapping to find bond price implied Q. For each corporate bond transaction in the sample, I could use equation (1.8) to find implied marginal Q with bond price b, coupon rate c, term to maturity m, and the risk free rate r. This is what Philippon (2009) does.

Although the first method seems appealing, the curvature of mapping depends on the model parameters (see the upper panel of Table 1.4). One misspecified parameter will bias against the significance and explanatory power of the implied Q. To perform this exercise carefully, we need to perform calibration for each firm. However, with an average of 13 years of annual observations for each firm, calibration is not promising.

The second approach provides a possible solution that is "calibration-free". Use $y(a_t)$ to replace b in equation (1.8), take logarithm on both sides, and we have the following results:[5]

$$log(I) \approx \Gamma + \frac{(n-1)\theta}{\gamma_-} log(CDS) - \frac{(n-1)\theta}{\gamma_-} log(y+m)(r+m) \tag{1.9}$$

with $\gamma_- = 0.5 - \frac{\mu}{\sigma^2} - \sqrt{(0.5 - \frac{\mu}{\sigma^2})^2 + \frac{2(r+m)}{\sigma^2}}$, and $\Gamma = log\left[\beta\left(\frac{n-1}{n\gamma}\right)\left(\frac{c+m}{\frac{c+m}{r+m} - \frac{\beta}{\psi}}\right)^{\frac{\theta}{\gamma_-}}\right]^{n-1}$.

Without losing any information in the model, this provides a simple log-linear relation. On the left side is the logarithm of investment. On the right side, the first term is a constant that contains the parameters of firm production and bond characteristics. The second term represents the logarithm of credit spreads. It provides the theoretical foundation to link the credit market prices with investment. The third term is an interaction term that captures the curvature between credit spreads and marginal Q. Previous studies (e.g. Miao and Wang (2010), Gomes and Schmid (2010), and Gilchrist et al. (2010)) use calibration and show that credit spread is linked to corporate bond prices, which affect investment through Tobin's Q. This decomposition carries the same key insight but clarifies the mechanism.

In equation (1.9), both q and bond yields y are simultaneously driven by the same shock process (see equations (1.3) and (1.7)). If a good shock ($da > 0$) arrives, the marginal Q will be larger, and the bond value will increase (mathematically $\frac{db(a)}{da} = A_- \gamma_- a^{-1+\gamma_-} > 0$). As the bond value increases, the yields y accordingly drop ($dy < 0$). It creates two effects in equation (1.9). The first is a "direct" marginal effect $\frac{(n-1)\theta}{(y-r)\gamma_-} dy > 0$ through the term $log(y-r)$. The economic interpretation is straightforward. Lower credit spreads mean better fundamentals. This will push up the optimal investment through the marginal Q. The second is

[5] Since we could always put the $log(r+m)$ in the first constant term, one question is whether the last term should be $log(y+m)$. Empirically, it does not matter. The reason to keep it in the last term is to create an analogue to (y-r)

an "adjustment" effect $\frac{-(n-1)\theta}{(y+m)\gamma_-}dy < 0$ through the term $log(y+m)$. This captures the important impact of nonlinearity, beyond a direct log-linear effect. In the end, the total marginal impact would be $\frac{(n-1)\theta}{\gamma_-}\frac{(m+r)}{(y-r)(y+m)}dy > 0$ for a good shock, and the first effect always dominates.

The elasticity of investment with respect to credit spreads $|\frac{(n-1)\theta}{\gamma_-}|$ depends on several parameters in the model. γ_- is a function of μ, σ and m. We can interpret μ as the firm sales growth, σ as the firm volatility, and m as the bond maturity.[6] With simple algebra (see Appendix Section A.1 for a formal proof), we have the following proposition:

Proposition 1 *The elasticity of investment with respect to credit spreads is high for firms with low growth rate μ and high volatility $\sigma$and for bonds with a long maturity.*

One way to think about the intuition is as follows. For the same level of shock, the firm with a high volatility or a low growth rate has a high default risk and hence high credit spreads. As the shock changes a small percentage, the changes in level of credit spreads are approximately the same. Since the level changes are the same, the percentage changes are low for the firm with high default risk. On the other hand, the shock and investment are linearly related. Thus, the elasticity of investment with respect to credit spreads is high for high risk firm, or the firm with a high volatility or a low growth rate.

The intuition for bond maturity is more involved. The information in the price of a long term bond has a longer time horizon than that of a short term bond. Suppose a unit of shock will arrive in future. This unit of shock will cause more percentage change in the short term bond price than in the long term bond price.

[6] The adjustment cost parameter n is not observable in the data. Here I focus on the observable characteristics.

The investment is driven by shock. The credit spread percentage change in long term bonds signals larger variation in the shock, and hence, the investment is more sensitive.

Interestingly, book leverage does not enter into the elasticity, but as shown in the upper panel of Table 1.4, it does affect the investment level.

Because of the closed form relation, we can use it to replace the unobservable marginal Q in the investment regression. The empirical specification is

$$log(I_{i,t}/K_{i,t-1}) = \beta_0 + \beta_1 log(CDS_{i,t-1}) + \beta_2 log(Int_{i,t-1}) + \beta_3 log(ctrl\, vars) + \epsilon_{i,t}. \tag{1.10}$$

CDS refers to credit spreads, and Int refers to the interaction term. The standard empirical literature takes a one-period lag of Q, so the credit spread term is also lagged in the regression. Widely used control variables include Q, leverage, firm size, cash flows, sales, and volatility. There are two reasons for taking the logarithm of investment-capital ratio. First, it is implied by the model. This is consistent with Abel and Eberly (2002) who show that the log-log specification, resulting from a nonlinear relationship between investment and fundamentals, produces more accurate predictions of investment than the linear specification. Second, as shown in Gilchrist and Zakrajsek (2007), investment data are positively skewed, which may create heteroskedasticity in $\epsilon_{i,t}$ across firms.

With $n - 1 \geqslant 1$, $\theta > 0$ and $\gamma_- < 0$, we should expect $\beta_1 < 0$ and $\beta_2 > 0$. Furthermore, we should expect the absolute value of β_1 and β_2 to be higher for firms with low growth and high volatility and for bonds with a long maturity. In the empirical section I use firm sales growth as a proxy for μ, and firm stock return volatility as a proxy for σ.

1.3 Data and Summary Statistics

Firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. The variable construction follows the standard literature, and the details are in Appendix Section A.5.

The bond trading and issue information comes from three sources. The main source is the Mergent Fixed Income Securities Database (FISD), which is considered the most comprehensive database of publicly offered bonds. U.S. insurance companies, which hold about 30%-40% of the value of all outstanding corporate bonds in the United States (see Hong and Warga (2000), Schultz (2001)), are required by the National Association of Insurance Commissioners (NAIC) to provide a record of all their fixed income transactions. the FISD contains such trading information from NAIC. These data represent actual transactions and not dealer quotes or matrix prices. In addition, the FISD provides details on bond issues since the 1950s, including the issuing and maturity dates, offering size, bond type, option features, rating, issuers, and so forth. Where possible, I use the rating information from Moody's in the FISD, and I use S&P rating if it is not available. I use bond trading information in the FISD for 1994 to 2010.

The second data source for bond trading is the Trade Reporting and Compliance Engine (TRACE), provided by the Financial Industry Regulatory Authority's (FINRA) over-the-counter corporate bond market real-time price dissemination service. In 2002, FINRA required bond transaction reporting for investment grade securities with an initial issue size of $1 billion or greater. In 2003 and 2005, FINRA expanded the requirements. Now, it represents over 99% of total U.S. corporate bond market activity. The trading face value is truncated at $1 million for speculative grade bonds and $5 million for investment grade bonds.

I use the truncated value as a proxy for the actual transaction size, and the descriptive statistics on transaction size are hence downward biased. However, this does not affect my later analysis.

The third data source for bond trading is from Lehman Brothers via the Fixed Income (or Warga) Database. This database has been widely used in the early literature (e.g. Duffee (1998), Collin-Dufresne and Goldstein (2001)). It contains month-end bond prices and is available from 1973 through 1998. See Hong and Warga (2000) for database details. Only observations with actual quotes are used, as matrix prices[7] are known to be problematic. I complement the trading information in TRACE and Lehman/Warga with the bond issue and rating information from FISD.

FISD and TRACE record daily trading, whereas the price in Lehman/Warga is month-end. Because the firm accounting information is from the COMPUSTAT annual database, the monthly frequency should be sufficient. I calculate the month-end price for each corporate bond in FISD and TRACE, merge them with Lehman/Warga, and then delete the duplicate entries.

After combining trading information from different sources, I clean up the data by the following steps. First, I keep only senior unsecured fixed coupon bonds. I drop callable, putable, asset-backed, exchangeable, or convertible bonds, because it is difficult to interpret the price of bonds that have additional features. Second, I drop bonds issued by financial companies (with a Standard Industrial Classification code between 6000 and 6999), as the model is inappropriate for them. Third, I drop bonds without rating information, maturity date, or issuance date to make sure the price is accurate. Last, because insurance companies are

[7] Lehman Brothers collects bid prices from its dealers for bonds that are either traded by the firm or tracked by one of its published bond indices. In months where no bid is posted, a matrix price is recorded as a “best guess”.

typically buy-and-hold investors, to reduce the illiquid effect in the price, I require the bonds to have trading information for at least 12 consecutive months. These procedures enhance the data quality. However, though not shown in this paper, the main empirical results do not depend on these cleaning steps.

Calculating credit spreads for each bond transaction requires caution. Some studies simply use Treasury yields with similar maturities as the risk free rates. However, this approach ignores the different convexities in those bonds, and the resulting credit spreads are accordingly biased.

To solve the problem, I take the following steps. First, for each transaction I create a security that comprises a set of zero coupon bonds that mimic the exact cash flows of this corporate bond. Second, I discount those zero coupon bonds to the transaction day by the Treasury zero-coupon yields estimated by Gurkaynak et al. (2007).[8] Third, I calculate the transaction yields of this risk free security using its price, transaction date, maturity date, and coupon rate, and then calculate the transaction yields of this corporate bond using its price, transaction date, maturity date, and coupon rate. Fourth, I denote the corporate bond yields y, the pseudo security yields r, the credit spreads $CDS = y - r$, and the interaction term $Int = (y+m)(r+m)$ where m is one over the bond maturity in years. Finally, I winsorize the data at 1% each tail for every year, and drop the observations with negative CDS.

The lower panel of Table 1.1 shows the bond characteristics. The data cleaning procedure sets a high bar for data selection and reduces the number of corporate bonds in the sample to 4917. The average issuance face value is about $424 million,

[8]Gurkaynak et al. (2007) estimate the U.S. Treasury yield curve from 1961 to date and their daily continuously compounded zero-coupon yields range from 1 year to 30 years. I interpolate those yields to get monthly data using cubic method so that on each transaction day we know the risk free discount factors for those cash flows. The data are available at http://www.federalreserve.gov/econresdata/researchdata.htm

and the median is $300 million. The offer prices are similar across bonds and close to face value. The median coupon rate is about 7%. The median maturity is 10 years. At the firm level, each firm issues about 10 bonds on average, but this number is positively skewed with a median of 8. This indicates that a few industrial firms are active in the public debt market. The average number of trades for each bond is about 66. Since the data are monthly, this number does not represent the real number of trades. Instead, it means that the bonds in sample are traded every month for at least 5.5 years on average.

Table 1.2 shows the summary statistics for bond trading. I define booms and recessions following the National Bureau of Economic Research definition. The median credit spreads during booms are about 140 bps and positively skewed with a mean of 210 bps. Credit spreads during recessions are much higher, with a median of 320 bps. This indicates that credit spreads contain important information about the economic fundamentals that drive firm investment. The interaction terms in booms and recessions are similar with medians of 0.022 and 0.021 respectively. The trading price is negatively related to spreads; therefore the prices are higher during booms. Age is defined as the number of years from the trading day to the bond issuance day. The median age is about 3 to 4 years; therefore the trades are usually made in the early days of a bond, given a median maturity of 10 years. The average bond rating is similar across different periods. The median of the numeric bond rating is about 8, which is equivalent to Moody's Baa1.[9] The median trading sizes are about $0.25 million (in face value) in booms and $0.11 million in recessions.

The lower panel of Table 1.2 presents the credit spreads for sub-samples. This

[9]The numeric values for bond ratings are 1 (Aaa), 2 (Aa1), 3 (Aa2), 4 (Aa3), 5 (A1), 6 (A2), 7 (A3), 8 (Baa1), 9 (Baa2), 10 (Baa3), 11 (Ba1), 12 (Ba2), 13 (Ba3), 14 (B1), 15 (B2), 16 (B3), 17 (Caa1), 18 (Caa2), 19 (Caa3), 20 (Ca), 21 (C), and 25 (D).

paper does not focus fixed income security pricing, but this lower panel serves as a crude test to see whether the credit spreads calculated are consistent with the findings in the existing literature. I define long term as term to maturity above 15 years, medium term as term to maturity between 7 and 15 years, and short term as term to maturity below 7 years. For the bond rating, I define prime grade as Aaa, high grade as Aa1 to Aa3, medium grade as A1 to Baa3, investment grade as Aaa to Baa3, and non-investment grade as below Baa3. Consistent with the literature, for investment grade, the long term bond spread is always higher than the short and medium term bond by about 10 to 20 bps across different sub-ratings, and the spread for high rating bonds is usually lower than that for low rating bonds.

A firm could have multiple bonds outstanding at the same time, and each bond may have trading records in several months in a year. To merge with annual firm accounting data from COMPUSTAT, an aggregation method is required. I choose the duration weighted average as the main proxy. The results are robust to different aggregation methods.[10]

The upper panel of Table 1.1 shows the summary statistics for the combined data. The sample comprises 809 firms, each of which has about 12 years of data , resulting in about 7500 observations. Because not many firms have access to the public debt market, it is interesting to compare sample firms with an average firm in the COMPUSTAT. The out of sample summary statistics are reported in the last three columns of Table 1.1. The most striking result is that sample firms are much larger than typical firms in the COMPUSTAT: for a sample firm the median asset value is about $5271 million (in 2004 dollars), whereas for an

[10] I tried the median, mean, Macaulay duration weighted average and modified duration weighted average.

out of sample median firm it is only \$137 million[11]- over 38 times smaller! In addition, sample firms have greater profitability, a higher dividend payout ratio, stronger cash flow, low stock return volatility, a less risky operation, and a better firm rating. On the other hand, they invest less, take more debt, rely less on equity financing, spend less on R&D, and have fewer cash holdings and tangible assets. These statistics suggest that sample firms are large and mature, they have easy access to the capital market, and they are unlikely to be subject to financial constraints.[12]

These results are further confirmed by the financial constraint indices. Financial constraint indices are widely used to explore cross sectional differences in the investment literature. I consider three popular indices here: SA index by Hadlock and Pierce (2010), WW index by Whited and Wu (2006), and KZ index by Lamont et al. (2001). The details are in the Appendix Section A.5. Before merging, I sort all firms (in and out of sample together) into five quintiles each year for the entire sample period. The least constrained group is assigned "1", and the most constraint group is assigned "5". Except for the KZ index (which is criticized by many papers, e.g. Whited and Wu (2006), Hadlock and Pierce (2010)), sample firms have a median value of 1. Even at the 95th percentile, this number is just 3 for the WW index and 2 for the SA index. This means that even the "most" constrained sample firm is not usually considered constrained in the literature. This is important because it suggests that the financial constraint may not be the first order effect that drives the investment. More analysis is provided in Section 1.5.

[11] I drop the firms with total book assets below \$10 million; therefore this result is not driven by tiny firms

[12] Acharya et al. (2012) find that the motive of precautionary savings could explain why firms with more cash holdings have higher credit spreads. The firms in distress are likely to have high cash reserves.

Table 1.3 shows the correlation matrix for the main variables in the sample. The p-value is reported in brackets. Investment negatively correlates with credit spreads, leverage, and recession, but positively correlates with the interaction term, Q, cash flows, sales, and profitability. A better rated firm (lower numeric value) tends to have lower credit spreads and higher investment. A more volatile firm is related to a high credit spread and a lower firm rating. These findings are consistent with the previous literature and predictions from the model. A more formal analysis is conducted in the next section.

1.4 Empirical Analysis

In this section, I first show the one-way and two-way data sorts, which provide preliminary evidence that supports the model. Second, based on equation (1.10), I run regressions to test the main prediction of the model. Third, I test Proposition 1 that different elasticities of investment with respect to credit spreads are related to different firm and bond characteristics. Fourth, I perform the robustness checks to determine whether the results hold for different cross sectional firm splits, sample period splits, and bond characteristics.

1.4.1 Data Sorting

The main prediction of the model is that credit spreads are negatively related to investment. Figure 1.1 provides preliminary evidence on one-way data sorts. In the upper panel, I sort firms into five quintiles based on their rating. On the x-axis, "1" represents firms with the highest rating, and "5" represents firms with the lowest rating. The right y-axis is the scale for investment and the left is for credit spreads. For each quintile, I report median credit spreads and investment.

We can see that as the firm rating goes down, firm investment drops. This may be explained by the model, as in the graph, credit spreads monotonically increase as the firm rating gets worse.

In the second panel, I sort firms into five quintiles based on their credit spreads. On the x-axis, "1" represents firms with the lowest credit spreads, and "5" represents firms with the highest credit spreads. Except for the first quintile, investment decreases monotonically as credit spreads increase. Meanwhile, credit spreads strongly and negatively correlate with Q, which is an empirical proxy for marginal Q.

Proposition 1 links the firm characteristics with elasticity of investment with respect to credit spreads. The lower panel in Table 1.4 presents the two-way sorts. In the middle panel, I sort firms into 5×5 portfolios by firm sales growth and credit spreads. For each portfolio, I report the median of investment. First, for each sales growth portfolio, the investment generally decreases as credit spreads increase, and the High-Low is always negative. Second, for each group sorted by credit spreads, firm with high sales growth invests more. Therefore, firms with high sales growth invest more and are less sensitive to credit spreads.

In the bottom panel, I sort firms into 5×5 portfolios by firm stock return volatility and credit spreads. The model predicts that for the same level of credit spreads, more volatile firms invest more. The data confirm this prediction. Investment generally increases as volatility increases in each portfolio sorted by credit spreads. Except for the last quintile, the High-Low is always positive. Therefore, firms with high volatility invest more and are more sensitive to credit spreads. On the other hand, after controlling for volatility, investment still decreases as credit spreads increase.

The results from data sorting support the model predictions. The next few sub-sections provide additional evidence.

1.4.2 All Sample

Petersen (2009) studies different estimation methods using corporate panel data, and finds that in the presence of both time and firm effects, the fixed effect and random effect models produce unbiased standard errors only when the effect is permanent and fixed. In addition, he suggests on page 458, "Since researchers do not always know the precise form of the dependence, a less parametric approach may be preferred. A solution is to cluster on two dimensions simultaneously (e.g., firm and time)." In this section, I use two-dimensional clustering estimator to run regressions. I also tried a fixed effect estimator with standard errors clustered at the firm level, and the results are not qualitatively different.

In the panel data, the firm fixed effect usually captures a large variation in investment. Empirically, it is the factor that produces the highest R^2 in regression. In equation (1.9), the first term is compounded into the firm fixed effect. To conservatively measure the explanatory power of credit spreads and the interaction term, I proceed as follows. First, I run a regression with pure firm fixed effects and denote the adjusted R^2 as R_1. Then, I add the regressors and denote the adjusted R^2 as R_2. The $R_2 - R_1$ expression measures the relative explanatory power of the variables we are interested in.

The first four columns of Table 1.5 present the results using the entire sample. All signs on credit spreads are negative and significant, and all signs on the interaction term are positive and significant. All p-values are less than 1%. The coefficients of credit spread and interaction terms are reasonably close. One possible reason the two coefficients are different is data aggregation. If they are aggregated by bond type, the coefficients become closer (as shown later). These results are consistent with the model predictions.

Tobin's Q has been widely used as a benchmark to measure firm investment opportunity. In this paper I argue that credit spreads should perform the same role. Thus, it is important to compare the R^2 of credit spreads with the benchmark. Empirically, credit spreads seem to do a better job than Tobin's Q. The R^2 of credit spread regressions is higher than that of Tobin's Q through all tables in this paper. Philippon (2009) finds a similar result at aggregate level, and provides two possible explanations. However, without empirical evidence, neither is fully satisfying. In Section 1.5, by using the richer data structure at the firm level, I provide the empirical evidence to explain this result.

In column (3) and (4), both credit spreads and Tobin's Q are significant, and they do not subsume each other. It suggests that neither is a perfect proxy for marginal Q. Both of them have the measurement error problems. Erickson and Whited (2000) discuss three sources of measurement error in Tobin's Q: (1) marginal Q is not equal to average Q; (2) average Q is not equal to Tobin's Q; (3) data limitation. In this paper, the measurement error in credit spreads is more likely to come from the first source. The first source is saying that a correctly specified model would break the equality. In this paper, I make two assumptions that make the model tractable: (1) no bankruptcy cost and no taxes; (2) the investment adjustment cost does not depend on the current capital stock level. Without those two assumptions, the analytical solution will break and we get nothing from the model. Nonetheless, they bring the measurement error.

In column (4), cash flow and sales significantly enter into the regression. The interpretation on the cash flow has a long tradition. Fazzari et al. (1988) is the seminal work in which they argue that the significant cash flow effect indicates that the financial frictions matter for firm investment. Furthermore, they argue that more financially constrained firms have a higher cash flow sensitivity in investment regressions. However, the recent literature takes a different view. Kaplan and Zingales (1997) find that the financial constraint sorting criterion in Fazzari et al. (1988) is problematic, and that more financially constrained firms have a lower cash flow sensitivity. Moyen (2005) reconciles the empirical results in both Fazzari et al. (1988) and Kaplan and Zingales (1997) in one model, and supports the conclusion in Kaplan and Zingales (1997). Gilchrist and Himmelberg (1995), Erickson and Whited (2000), and Cummins et al. (2006) show that the cash flow effect results from the mis-measured Tobin's Q. Gomes (2001), Alti (2003) and Eberly et al. (2009) find that the significance or the sensitivity of cash flow could have nothing to do with the financial constraint. In summary, the effect of cash flow merely reflects the measurement error in the proxy for marginal Q. When the proxy is not perfect, any variables that co-vary with the state variables in marginal Q would show up significantly in investment regressions. With a similar insight, Gala and Gomes (2012) use the tensor product of sales to replace the Tobin's Q in the investment regressions, and find a better fit. The significance of cash flow and sales in column (4) is consistent with the finding that neither credit spreads nor Tobin's Q is a perfect proxy for marginal Q.

Because of the presence of the interaction term, the investment percentage changes with respected the changes in credit spreads must be calculated carefully. In terms of magnitude, the median credit spreads in sample are 180 bps, median maturity is 10 years, the median pseudo security yields are about 436 bps, and median investment is about 9%. For a 50 bps increase in corporate bond yields (half the size between mean and median of credit spreads in the sample), the direct marginal effect through the credit spread term implies a decrease of investment from 9% to 8.47%. The indirect effect through the interaction term implies an increase to 9.04%. The direct effect dominates, and the investment should be 8.43%.[13] Although it looks relatively small, the indirect effect could be important depending on the sample. Ignoring the interaction term could overstate the impact of credit spreads on investment.

The empirical measure of credit spreads may contain components other than default risk. To extract the default component, I follow Almeida and Philippon (2007) and construct an alternative measure $CDS^A_{i,t,} = CDS_{i,t} - 0.51\%$. The 0.51% is the average 1 year AAA corporate bond spread over Treasuries for 1985 to 1995, estimated by Almeida and Philippon (2007). It represents pure taxes and liquidity effect.

The last four columns in 1.5 report the results using this alternative measure. The results do not change much. Both credit spreads and the interaction term are significant and have the expected sign. The R^2 is slightly smaller, but the coefficients of the two terms are close. Because there is not much change, I use the main measure throughout the rest of the paper.

I also try an alternative estimation method to run the regressions, and the results are robust. The four columns in Table 1.6 present the estimates using the firm fixed effect estimator with standard errors clustered at firm level. Both credit spreads and the interaction term are significant, and have the expected sign. The R^2 from the credit spread regression is higher than that from the Q regression. Compared to the first four columns in Table 1.5, actually the coefficients on credit spreads and interaction term become larger, and standard errors become smaller. The firm fixed effect estimator generates more significant results.

[13] I use the coefficients in the first column. According to the model, when the credit spreads change, the shock must has changed. The variation in shock will lead change in Q. So in column (3) and (4), we can not hold Q constant if we assume an increase in bond yields.

For the overall sample, the regression results largely support the model predictions. Credit spreads signal investment opportunity, like the widely used Q, and its predictive power is even higher.

1.4.3 Characteristics and Elasticities

The model predicts that the elasticity of investment with respect to credit spreads is high for firms with a low growth and a high volatility and for the long term bonds. In this section I examine cross sectional firm level data to test these predictions. I use firm sales growth as a proxy for μ, and firm stock return volatility as a proxy for σ.

Before the analysis, three points are worth making. First, the early literature (e.g. Cummins and Hassett (1992)) tries to recover the capital adjustment cost parameters from the regression coefficient on Tobin's Q. However, Whited (1994), Erickson and Whited (2000), and Eberly et al. (2009) point out that it is ineffectual to use regressions to estimate the adjustment cost parameters. Abel and Eberly (2011) show that the coefficients on the cash flow and Tobin's Q could have nothing to do with the adjustment cost. In my model, the adjustment cost parameters are β, γ and n. They are not identifiable from the coefficients in the regression. Hence, I do not discuss the implied adjustment cost in the paper.[14] On the other hand, the coefficient itself is not meaningless (Whited (1994)), so I use the cross sectional predictions as an additional channel to test the Q theory.

Second, Proposition 1 implicitly assumes that the firms have the same adjustment cost parameter n. There might be a large cross sectional variation of this parameter. Nonetheless, there are two reasons why it may not materially affect

[14] An appropriate way to estimate adjustment cost parameters may be the Indirect Inference, e.g. Simulated Method of Moments. However, the size of those parameters is not the focus of this paper.

the empirical analysis in this section. First, the sample firms being studied are giant and mature, and they have strong dividend payout. They tend to be more homogenous than a group of random firms in COMPUSTAT. Eberly et al. (2009) study a similar sample of firms and find that the model could fit data well without assuming heterogeneous adjustment cost parameters. Second, the standard literature (e.g. Abel and Eberly (1994)) assumes that the adjustment cost is independent of the shock process. If the cross sectional difference in adjustment cost is random, it will not affect the results.

Third, Proposition 1 uses the investment level, but empirically the independent variable is the investment ratio. This will not affect the inference much. First, the capital stock is lagged one period, so it is predetermined. Given a capital stock level, the intuition behind the elasticity does not change. Second, what is more important, the empirical setting is a log-log specification. Using the investment ratio is equivalent to subtracting the logarithm of capital stock from both sides in equation 1.9. It does not affect the elasticity $|\frac{(n-1)\theta}{\gamma_-}|$.

Table 1.7 presents the estimates for low and high sales growth firms. I sort the firms into three terciles based on their sales growth. Columns (1) to (4) contain the estimates for the first quantile (low growth), and columns (4) to (8) contain the estimates for the third quantile (high growth). First, credit spreads and the interaction term are generally significant and have the expected sign. R^2 is higher for the credit spread regressions.

Second, as the model predicts, the loadings on credit spreads and the interaction term are higher for firms with low sales growth. The intuition is explained in Section 1.2. This is direct evidence that supports the model. In the bottom panel, I perform a formal Chow test, and the coefficient differences between the two groups (the first and third terciles) are generally statistically significant. One reason not all of them are significant is that sales growth is not accurately measured in this unbalanced short panel. Because volatility is estimated using high frequency monthly data, the results of the next test are sharper.

The median investment for low sales growth firms is about 7% and is 12% for high sales growth firms. In both groups, the median credit spreads are about 183 bps, median bond maturity is 10 years, and the median pseudo security yields are about 436 bps. With these medians, a 50 bps increase in corporate bond yields signals a reduction in investment to 6.55% for low growth firms and to 11.3% for high growth firms. Though low growth firms are more sensitive to spreads, it is the high growth firms that drop more in investment. This is because the investment level in high growth firm is also high in the data.

Table 1.8 presents the estimates for low and high volatility firms. I sort the firms into three terciles based on their volatility. Columns (1) to (4) contain the estimates for the first quantile (low volatility), and columns (4) to (8) contain the estimates for the third quantile (high volatility).

The credit spreads and the interaction term in all specifications are significant and have the expected sign. The coefficients on credit spreads and the interaction term are higher for firms with high volatility. The intuition is explained in Section 1.2. Furthermore, in the bottom panel, all differences are statistically significant at least at 5% level.

Median investment is 8.52% for low volatility and 8.84% for high volatility firms. The median credit spreads are about 126 bps for low and 329 bps for high volatility firms. Median bond maturity is 10 years, and the median pseudo security yields are about 440 bps. With these medians, a 50 bps increase in corporate bond yields signals a reduction in investment to 8.17% for low volatility firms and to 8.34% for high volatility firms. High volatility firms invest more, are more sensitive to credit spreads, and decrease investment more when an unfavorable shock hits. This also could explain why these firms are more volatile.

The last prediction addresses to bond characteristics, and the results are reported in Table 1.9. The first four columns show the results when using only short and medium term bonds are used, and the last four columns show the results when using only long term bonds. The interaction term for long term bonds is not significant, but the other predictions still hold. The investment should be more sensitive to credit spreads of long term bonds. This is true for all specifications, and the all differences are statistically significant at the 1% level.

1.4.4 Robustness Check

In this section I perform a robustness check to see whether the results hold when the sample is split in different ways. First, I use the WW and SA financing constraint indices[15] to split the sample cross sectionally. Interestingly, the difference in elasticity of investment with respect to credit spreads between groups can be explained by their firm characteristics (namely, growth and volatility).

Table 1.17 shows the results for splitting the sample by the WW index, and Table 1.18 shows the results for splitting by the SA index. I sort firms into three terciles by index, and the first (third) quantile is the less (more) constrained group. In both tables, the first four columns are for less constrained firms, and the last four columns are for more constrained firms. Here, I use the word "constrained", but it does not necessarily mean that the firms are indeed constrained. It is a relative measure, not absolute. Actually I show in the next section, that the firms in my sample are unlikely to be constrained. The purpose of using these indices

[15] SA index is from Hadlock and Pierce (2010), and WW index is from Whited and Wu (2006). See Section Appendix A.5 for details.

is to see whether the predictions hold for different samples.

The coefficients of credit spreads and the interaction term are all significant and have the expected sign. Furthermore, elasticity of investment with respect to credit spreads is usually higher for more constrained than less constrained firms. The model does not predict this. The bottom panel of Tables 1.17 and 1.18 reports firm characteristics for these two groups. For the WW index, it is clear that less constrained firms have high sales growth and low volatility. This is the type of firm that has low elasticity. The results for the SA index are mixed: less constrained firms have low sales growth but also low volatility. One reason may be that volatility dominates. In addition, because these two effects work in opposite directions, this may explain why the difference between the SA index groups is not as sharp as that for the WW index.

Tables 1.17 and 1.18 also provide evidence that the firm financial constraint status is not driving the results. The model predictions hold in both "more" and "less" financially constrained groups. Section 1.5 gives a further analysis.

Tables 1.10 and 1.11 provide results for different periods and different bond ratings. The main prediction holds for both booms and recessions and for both investment grade and speculative grade bonds. The results are robust.

Table 1.12 looks at whether bond liquidity drives the results. Following Bao et al. (2011), I construct an individual bond liquidity measure. Let $p_t = ln(P_t)$ where P_t is the bond price. Then the liquidity $\gamma = -Cov\left[(p_t - p_{t-1}),\, (p_{t+1} - p_t)\right]$. The higher the γ, the more illiquid the bond is. Table 1.21 shows how this measure predicts credit spreads. In column (2), γ is positive and statistically significant. This means that when a bond is more illiquid, spreads will be higher. However, this explains little variation in the spreads with an R^2 that is smaller than 0.5%. This suggests that bond liquidity is unlikely to drive the predictions in this paper.

Based on this measure, I sort the bonds into three terciles . The first four columns in Table 1.12 contain estimates using only high liquidity bonds (first quantile), and the last four columns contain estimates using low liquidity bonds (third quantile). Although the magnitude of coefficients changes a little, the basic results still hold.

I also test the model at the aggregate level and find strong supporting evidence. The details are available in the Online Appendix.[16]

1.5 Discussion: Why Better?

This paper finds that credit spreads explain more variation of firm investment than the widely used benchmark Tobin's Q. This is consistent with the aggregate evidence in Philippon (2009). Intuitively, given the curvature of the payoff functions, it is the stock price that should be more sensitive to changes in firm fundamentals. This result seems puzzling and there is no systematic study yet to explain it. This section tries to fill this gap. I test four possible explanations. Because they are not mutually exclusive, the goal here is to find the likely main driving force(s).

1.5.1 Option Value

The first explanation, as proposed by Philippon (2009), is that the option value affects the equity price (and hence the Tobin's Q), but not the investment and bond price. This weakens the correlation between the investment and Tobin's Q. I find that this explanation is not convincing. Theoretically, it may go both ways and depends on the assumptions. For example, if the firm has a defaultable

[16] It can be found at https://dl.dropbox.com/u/21495042/TaoShen/Research.html

perpetual bond (e.g. Goldstein et al. (2001)), then the option value ought to affect the bond price as well. Intuitively, all else equal, any changes of state variables that increase the equity price should decrease the bond price. Empirically, the firms being studied in the paper are large and mature (see Table 1.16), and the growth option may be a small portion in total equity value.

I formally test this explanation. Following the standard literature (e.g. Barclay et al. (2006), and Albuquerque (2012)), I use Tobin's Q and the ratio of R&D expense to total assets as two proxies for the option value. Arguably, the higher the proxy value, the higher the portion of growth option value in total equity value.

Based on one of these two proxies, I sort firms into terciles in each year. The firms in the first (third) tercile have the lowest (highest) option value. If the option value is the reason for the better performance of credit spreads, then credit spreads and Tobin's Q should have similar performance for the firms in the first tercile, and credit spreads should outperform Tobin's Q only for firms in the third tercile. Table 1.13 reports the estimates in two panels. The upper panel uses Tobin's Q as a proxy, and the lower panel uses the ratio of R&D to total assets as a proxy. The evidence is mixed. In the upper panel, the explanatory power of Tobin's Q is smaller than that of credit spreads in both first and third terciles. There is no evidence that the option value could explain the difference. However, in the lower panel, there is some supporting evidence. The performance of credit spreads is about the same across the two terciles. For firms with low option value, the explanatory power of credit spreads and Tobin's Q are close. For firms with high option value, the explanatory power of Tobin's Q drops from 13% to 6%.

To reconcile these inconsistent results, I further require the firms in the upper panel to have R&D information available. Though not reported in the paper, the results do not change much. Because different proxies yield different results and both of them are widely used, the inconsistent empirical evidence suggests that option value may not be the key driving force.

1.5.2 Equity Mispricing

Philippon (2009) proposes another explanation, equity market mispricing. This argument is not so obvious. Empirical and theoretical evidence supports the idea that mispricing is more likely to happen when returns are positively skewed (e.g. Barberis and Huang (2007)). Compared to stock returns, bond returns are more positively skewed (e.g. Cappiello et al. (2006)).

To test this explanation, I follow the approach in Stambaugh et al. (2012) who use the market-wide investor sentiment index constructed by Baker and Wurgler (2006) to explore sentiment effects on stock returns. They find that equity mispricing is more prominent during high sentiment periods, due to the short selling constraint. By using the same sentiment index, I split the sample by high and low sentiment periods. If the bond price is less noisy than the equity price, we should expect that (1) the performance of credit spreads and Tobin's Q should be similar in low sentiment periods, and credit spreads outperform Tobin's Q in high sentiment periods; (2) the performance of credit spreads should be similar across the two periods.

Table 1.14 shows the estimates by sentiment periods. Neither of the predictions above hold. First, the explanatory power of credit spreads is higher than that of Tobin's Q in both periods. In the low sentiment period when there is less equity mispricing, the credit spreads still outperform the Tobin's Q. Second, the explanatory power of credit spreads drops by half in the high sentiment period. The bond price is not immune to market-wide sentiment. These two findings suggest that equity mispricing may not be the reason for the better performance of credit spreads, and that the credit market price also suffers from a potential mispricing problem.

1.5.3 Financial Frictions

Because the two existing explanations seem unconvincing, I propose a third one in this paper. Hennessy et al. (2007) show in a model that, in the presence of financial frictions, there is a wedge between marginal and Tobin's Q. While the marginal Q is still a sufficient statistic for optimal investment, Tobin's Q is not. One possible explanation for the better performance of credit spreads is that they pick up the impact of this wedge of financial frictions.

To test this explanation, I proceed in two steps. First, I show that the connection between this wedge of financial frictions and credit spreads is stronger than that of Tobin's Q. Second, I show that this wedge drives the difference between the performance of credit spreads and Tobin's Q.

Particularly, I examine two types of financial frictions in Hennessy et al. (2007): costly external financing and debt overhang. Firms with costly external financing have limited access to new debt, hence rely heavily upon external equity for financing and pay little or no dividend. The theoretical foundation for limited access to debt markets could be adverse selection (e.g. Stiglitz and Weiss (1981)), and/or moral hazard (e.g. Hart and Moore (1994)). Myers (1977) points out the debt overhang problem. Preexisting defaultable debt makes the first-best investment provide a positive spillover to the debt holders, leading to underinvestment.

Connection

Following the standard literature (e.g. Hennessy et al. (2007)), I use a financial constraint index as a proxy for costly external financing, and use the terms "financial constraints" and "costly external financing" interchangeably. There are two popular indices: the SA index by Hadlock and Pierce (2010), and the WW index by Whited and Wu (2006).[17] The WW index is a weighted sum of several firm accounting variables, which suffer from endogeneity problems. The SA index is a weighted sum of firm's size and age, both of which tend to be exogenous. The index details are in Section A.5 in Appendix.

In the upper panel of Table 1.15, I sort the firms into five quintiles based on either the SA or WW index, and report the mean and median of credit spreads and Tobin's Q in each quintile. For both the mean and median, there is a clear monotonic pattern in credit spreads: more constrained firms have higher credit spreads. It is true for both WW and SA indices. In contrast, except the mean in WW index, there is no clear pattern for Tobin's Q across five firm quintiles.

In the lower panel of Table 1.15, I run regressions to further test the connection. The dependent variable is either credit spreads or Tobin's Q. The independent variables are indices and their squared terms. First, both indices have significant correlation with credit spreads, and large explanatory power in explaining the variation in credit spreads. The R^2 is as high as 27%. The correlation is even stronger for the SA index, which is considered more exogenous. Second, both indices have weak correlation with Tobin's Q, and the R^2 is at most 2%. The two panels suggest that the connection between financial constraint and credit spreads is stronger than that of Tobin's Q. Empirically, credit spreads capture the effects

[17]KZ index by Lamont et al. (2001) is criticized for including the Tobin's Q as part of the index (Whited and Wu (2006)).

of costly external financing better.

Debt overhang is most pronounced for firms with high leverage, high default probability, and high recovery ratio in default. The exact computation of the overhang term is highly prone to measurement errors: it involves predicting a firm's default probabilities for the next twenty years, and estimating the recovery ratio. The default probability is usually estimated from bond ratings (e.g. Hennessy et al. (2007), in which another step of rating imputation is required if missing) or a Merton type structural model (e.g. Alanis and Chava (2012). See Section A.2 in Appendix for details.). The recovery ratio is usually an estimate based on two-digit SIC from Altman and Kishore (1996).

Because the computation is error-prone and the overhang term itself is not of central interest, I do not compute the overhang term but use proxies to test the connection. Assuming that the recovery ratio is exogenous to both credit spreads and Tobin's Q, I use distance-to-default and book leverage as proxies. Compared with the existing methods, the best proxy for default probability is arguably the firm credit spread. It is a measure directly from the credit market price and has less measurement error.[18] Equity price based distance-to-default makes the result favor Tobin's Q.

In the upper panel of Table 1.19, I run regressions in which the dependent variable is either credit spreads or Tobin's Q, and the independent variables are distance-to-default and book leverage. Surprisingly, distance-to-default explains more variation in credit spreads than Tobin's Q. Book leverage explains less than 1% of variation in Tobin's Q, while this number for credit spreads is 9%. Both proxies are more connected to credit spreads than Tobin's Q.

[18] The rating approach relies on the information of a rating agency, imputation of missing bond rating, and the procedure to transfer rating to default probabilities. The structural approach relies on equity prices, a particular Merton type model, and a complex algorithm.

Because the overhang term is not computed explicitly, I show that credit spreads do capture the impact of overhang through a three-step process. First, in each year I sort firms into terciles based on the default probabilities, proxied by firm credit spreads, book leverage, and the product of default probabilities and book leverage. The firms in the first tercile have the smallest debt overhang problem, while the firms in the third tercile have the greatest overhang problem. Second, I project the credit spreads and the interaction term onto the space of Tobin's Q (including the level, logarithm, and squared term of Tobin's Q) and financial constraints (both WW and SA indices, and their squared terms). The projection residuals should be largely the debt overhang term according to Hennessy et al. (2007). Third, I use the residuals of credit spreads and interaction term to predict the investment in the first and third tercile sorted by those three proxies. We should expect that the residuals are significant and important in the third tercile, and less significant and important in the first tercile.

The lower panel of Table 1.19 reports the results. For firms with a smaller overhang problem, residuals of credit spreads have small coefficients and are not even significant in columns (1) and (3). Their explanatory power is small. For firms with a larger overhang problem in the last three columns, the coefficients become large and all of them are significant. The explanatory power is also doubled.

The evidence in Table 1.19 shows that debt overhang is more connected to credit spreads, and credit spreads do capture this overhang effect.

Impact

In this part I show that this wedge drives the difference between the performance of credit spreads and Tobin's Q. Interestingly, debt overhang seems the key force, and the impact of financial constraint is tiny.

Table 1.1 provides the evidence suggesting that the sample firms are unlikely to be financially constrained, as discussed in Section 1.3. Table 1.16 shows more detailed results. I sort the out-of-sample firms into five quintiles based on the WW index (in the upper panel) and the SA index (in the lower panel). The quintile of the least constrained firms is denoted 1, and the quintile of the most constrained firms is denoted 5. Financial constraint would largely affect the investment of the most constrained firms. The least constrained firms have sufficient funding or could borrow at favorable rates to finance their investment. The investment of less constrained firms should depend more on whether good projects exist and less on whether the financing costs are high.

In both panels of Table 1.16, the first two columns show summary statistics for sample firms. In-sample firms are much larger than out-of-sample firms. For the least financially constrained out-of-sample firms, the median firm size is about \$2697 million, about half of the size of a median sample firm! For firm age, the median sample-firm is about 10-20 years older than the median least constrained out-of-sample firm. The median dividend payout ratio for in-sample firms is 16%, higher than that of the least constrained firms (13.7%), and much higher than the other groups that have almost zero payout. Those statistics suggest that the firms in the sample have few, if not zero, of the characteristics that would make them constrained by the criteria of the standard literature.

Besides the descriptive statistics, the empirical tests provide additional support. If financial constraints are the reason, credit spreads and Tobin's Q should have similar explanatory power for the less constrained firms, and credit spreads outperform Tobin's Q for the more constrained firms. Table 1.17 and 1.18 show that there is no such evidence. Actually, for both indices, the difference of explanatory power between credit spreads and Tobin's Q is smaller for the more constrained group.

I find that debt overhang is likely the key driving force. In Table 1.20, I sort firms into terciles based on the the product of default probabilities and book leverage. The default probability is proxied by firm credit spread. The firms in the first (third) tercile should have smaller (greater) debt overhang problem. In column (1) and (2) for firms with smaller debt overhang, the explanatory power of credit spread is 8%, which is very close to the 6.9% of Tobin's Q. In column (5) and (6) for firms with greater debt overhang, the explanatory power of credit spreads increases to 13.5%, while this number for Tobin's Q is 7.3%, which is barely changed. Across the two terciles, we can see that (1) the performance of Tobin's Q is similar; (2) the performance of credit spreads is better for firms with high debt overhang; (3) the performance of credit spreads and Tobin's Q is close for firms with low debt overhang. These findings suggest that debt overhang seems to be the key force.

One important caveat is that all the tests for the possible explanations of the better performance of credit spreads are suggestive. These three explanations are not mutually exclusive. It is very likely that multiple forces are working simultaneously, and their relative importance may depend on the firms in the sample. Furthermore, the proxies in the tests are noisy, and may be correlated with each other. For example, in the data Tobin's Q and credit spreads are negatively correlated. Option value is proxied by Tobin's Q, and default probability is proxied by credit spread. Thus, empirically firms in the sample with greater overhang (high default probability) tend to be similar to firms in the sample with low option value. Theoretically, debt overhang and option value are very different and their relation may not be obvious.

These suggestive conclusions are still useful. They shed light on how to construct the model. This paper presents a tractable model, which provides a theoretical foundation for using credit spreads as a proxy for marginal Q. However, it is not rich enough to explain why credit spreads are better. Based on the evidence, it seems that incorporating financial frictions in the model is a promising way to get a deeper understanding of the empirical results.

1.5.4 Distance to Default

Tobin's Q is a special way to use equity market information. The fourth possible explanation is that equity markets do provide sufficient information for marginal Q, but Tobin's Q fails to capture it. The basic idea is as follows. In the model, it is the shock that drives the investment. When the shock is close to (far from) the default boundary, the firm invests less (more). The Distance to Default (DD) drives the results, and credit spreads are a natural empirical candidate for the DD. However, based on the Merton-KMV model, we can also calculate the DD using equity market information. This approach has two potential advantages. First, it would greatly enlarge the sample of firms, as its calculation involves only equity prices and balance sheet information. Second, the comparison with the credit spreads regressions is more fair, as Q is not a direct measure of DD.

With this insight, I calculate the DD for sample firms using a complex procedure. The theoretical derivation and empirical algorithm are in Section A.2 in Appendix.

I first run the regressions to see whether the constructed DD can predict credit spreads for sample firms. Table 1.21 presents the results using monthly firm credit spreads and the DD. For all specifications, the DD is very significant and has the expected negative sign (the higher the DD, the lower the credit spreads).

Furthermore, the DD alone explains 36% of the variation in credit spreads. This is a relatively large number for panel data regressions. This suggests that this equity market based empirical measure indeed captures the idea of the DD.

Next, I use the equity market based measure to predict investment. Table 1.22 shows the results. First, it does predict investment. In the first three columns, the coefficient of this measure is positive and significant. Second, however, when we add both credit spreads and Q in the regressions, the equity market based measure becomes insignificant. In addition, its R^2 in column (1) is less than half the size of in the credit spread regression.

The equity market based DD does not perform as well as credit spreads. Tobin's Q seems to capture equity market information about the firm investment.

1.6 Conclusion

The traditional investment literature has focused on the information content in the equity market while largely ignoring the credit market. Intuitively, much like Q, credit spreads should reflect future productivity and hence predict investment. In the current paper, I formalize this idea by constructing and testing a model in which an analytical log-linear relation is established between marginal Q and credit spreads. In addition, in my model elasticities of investment with respect to credit spreads are associated with firm and bond characteristics: elasticity is high for firms with low growth and high volatility, and for bonds with long maturity. This finding is unique to my model, as the standard investment model links only investment-Q sensitivity to unobservable firm adjustment costs.

Empirical results largely support the model. The investment and credit spreads are strongly negatively correlated, the R^2 from the credit spread regression is consistently higher than the R^2 from the benchmark Q regression. Moreover, the cross sectional difference in elasticity of investment with respect to credit spreads can be explained by firm and bond characteristics.

To understand why credit spread is a better proxy for marginal Q, I test four possible explanations. I find that credit spreads capture the effects of financial frictions which drive a wedge between marginal and Tobin's Q. Because Tobin's Q is not a sufficient statistic for investment in the presence of financial frictions, this may explain the better performance of credit spreads.

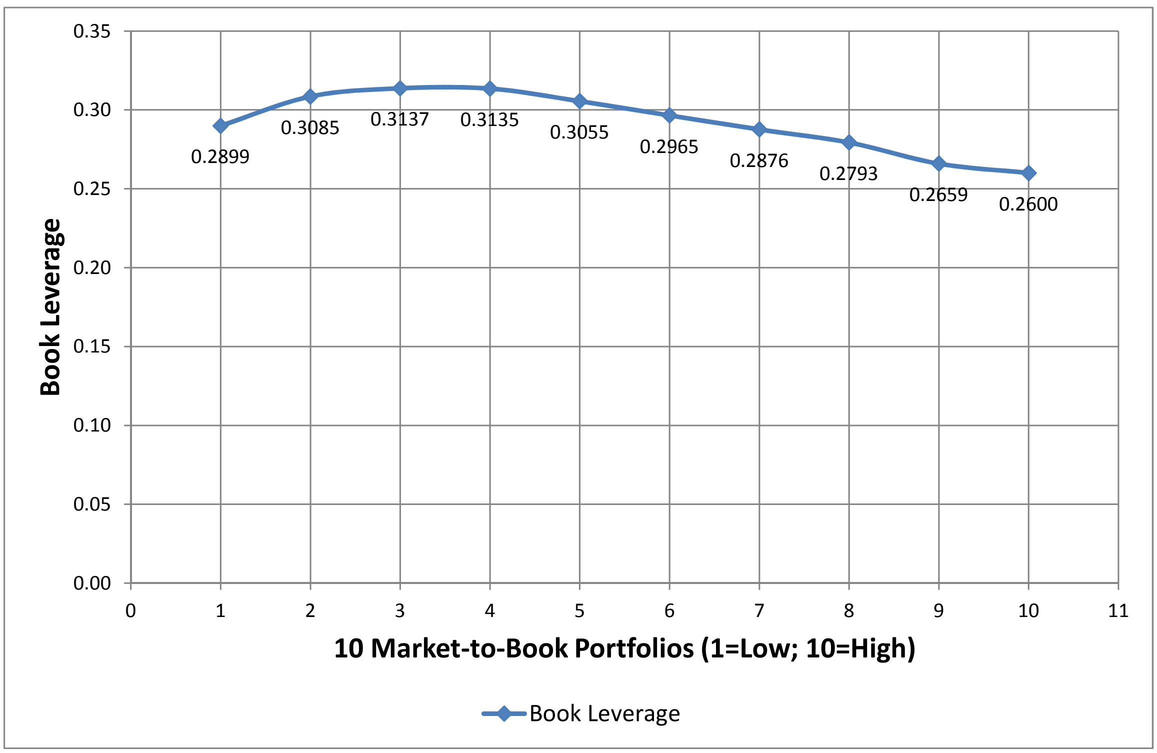


Figure 1.1: Book Leverage Across Ten Market-To-Book Portfolios

Every year, we sort firms into 12 quantiles basing their market-to-book ratios. Then the median book leverage ratio of each quantile over all sample period is plotted. We drop the medians from first and the last quantiles, and plot the rest. "1" represents the portfolio with the lowest market-to-book ratio, while "10" represents the one with the highest market-to-book ratio.

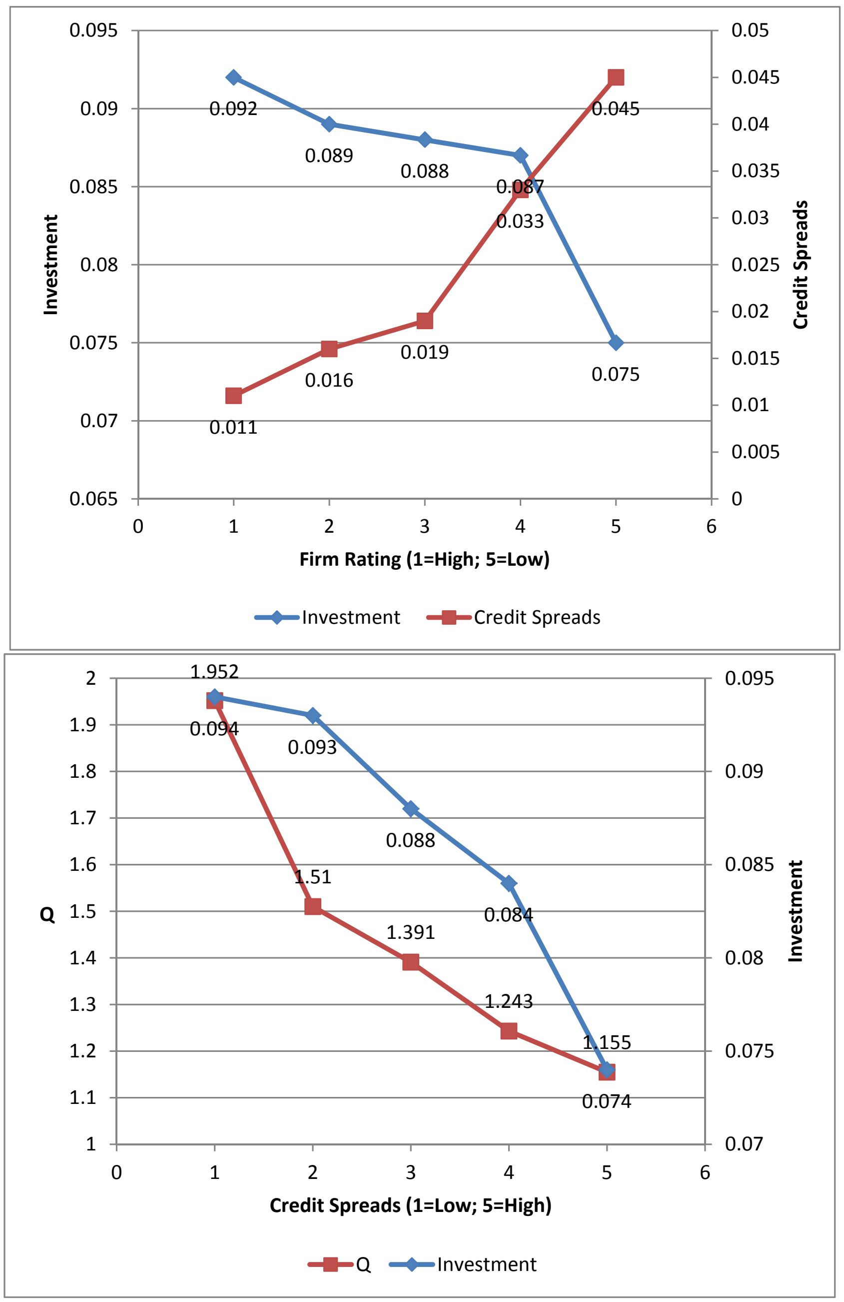


Figure 1.2: Investment, Firm Ratings, Q and Credit Spreads

Every year, we sort firms into 5 quantiles basing their credit spreads and ratings. Then the median Q and investment ratio of each quantile over all sample period is plotted. In the upper panel, the left Y-axis is the scale for investment, and right Y-axis is for credit spreads. On X-axis, "1" represents the portfolio with the best ratings, and "5" is the one with the worst ratings. In the lower panel, the left Y-axis is the for Q, and right Y-axis is for investment. On X-axis, "1" represents the portfolio with the lowest spreads, and "5" is the one with the highest spreads.

Table 1.1: Descriptive Statistics

In the upper panel, the firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. The lower panel provides the summary for bond characteristics. Issuance Size is the offering quantity in terms of units. One unit bond has a face value of $1000. Offer Price is the initial offer price at a $100 basis. #Trades is the number of credit spreads observations for each bond in sample. #Bond per Firm is the number of outstanding bonds for each issuing firm. The variable details are in Section 1.3.

	In Sample						Out of Sample		
	n	mean	median	sd	5%	95%	mean	median	sd
I/K	7573	0.115	0.090	0.106	0.030	0.272	0.230	0.122	0.337
Q	7573	1.667	1.405	0.932	0.887	3.229	1.914	1.368	1.618
CDS	7558	0.028	0.018	0.034	0.007	0.076	N/A	N/A	N/A
Int	7558	0.028	0.024	0.018	0.010	0.059	N/A	N/A	N/A
Cash/K	7566	0.198	0.152	0.481	-0.039	0.635	-0.080	0.141	1.696
CH/K	7572	0.278	0.073	1.020	0.004	0.943	1.385	0.201	3.875
Leverage	7558	0.235	0.204	0.148	0.048	0.535	0.189	0.134	0.191
Book Leverage	7573	0.320	0.293	0.164	0.106	0.631	0.234	0.191	0.222
log(Size)	7573	8.555	8.574	1.147	6.615	10.286	5.113	4.918	1.732
Sales/K	7573	2.932	1.670	5.492	0.290	7.399	5.006	2.621	7.539
Profitability	7565	0.336	0.235	0.543	0.055	0.978	0.130	0.209	1.566
Firm Rating	7467	11.606	11.000	3.531	7.000	17.000	13.958	15.000	4.006
Payout	7565	0.246	0.162	0.288	0.000	0.802	0.120	0.000	0.283
Equity Issuance	7283	0.012	0.003	0.031	0.000	0.055	0.054	0.003	0.137
R&D	4145	0.072	0.030	0.129	0.000	0.302	0.541	0.107	1.241
Tangibility	7478	0.403	0.424	0.104	0.201	0.533	0.462	0.495	0.103
KZ Index	6917	3.206	3.000	1.265	1.000	5.000	3.033	3.000	1.413
WW Index	7558	1.270	1.000	0.594	1.000	3.000	3.229	3.000	1.345
SA Index	7573	1.156	1.000	0.434	1.000	2.000	3.190	3.000	1.339
HHI Index	7573	0.178	0.135	0.156	0.042	0.489	0.161	0.120	0.138
Volatility	7101	0.366	0.317	0.196	0.173	0.731	0.556	0.488	0.309
	Number of Firms 809			Average Time Length 12.908					

	Bond Characteristics				
	mean	median	sd	5%	95%
Issuance Size	424165	300000	421548	100000	1200000
Offer Price	99.496	99.742	2.136	98.590	100.000
Coupon	6.989	6.875	1.802	4.400	9.900
Maturity	13.009	10.000	11.068	4.917	30.000
#Trades	66.197	59.000	36.739	20.000	133.000
#Bond per Firm	10.711	8.000	10.139	1.000	26.000
No. of Bonds	4917				

Table 1.2: Summary Statistics: Credit Spreads

The credit market information comes from different sources. CDS is the credit spreads and Int is the interaction term. Price is the trading price at $100 basis. Age is the number of years between the trading day and issue day. Rating is the Moody's bond rating in numeric values. See footnote9 for details. Trading Size is the number of bond units in each trade. Each unit has a face value of $1000. Definition of booms and recessions follows NBER. Define long term as the term to maturity above 15 years, medium term as between 7 and 15 years, and short term as below 7 years. Define prime grade as the ratings of Aaa, high grade as the ratings from Aa1 to Aa3, medium grade as the ratings from A1 to Baa3, investment grade as the ratings from Aaa to Baa3, and non-investment grade as the ratings below Baa3. The detail information of database, data cleaning, and variable construction is in Section 1.3.

	Booms						Recessions					
	n	mean	median	sd	5%	95%	n	mean	median	sd	5%	95%
Credit Spreads	221307	0.021	0.014	0.025	0.005	0.056	47027	0.049	0.032	0.061	0.012	0.141
Interaction	221307	0.028	0.022	0.025	0.007	0.067	47027	0.026	0.021	0.023	0.007	0.061
Price	222730	103.052	103.000	11.615	87.236	119.434	47614	94.713	99.400	15.763	62.900	110.309
Age	222730	4.566	3.417	5.101	0.250	12.333	47614	5.316	4.167	5.242	0.250	14.750
Rating	222730	8.265	8.000	3.465	3.000	15.000	47614	8.990	9.000	3.647	4.000	16.000
Trading Size	154027	1697.849	250.000	4137.377	5.000	8000.000	44713	1341.744	110.000	3747.067	5.000	5001.000

	Short and Medium Term						Long Term					
	n	mean	median	sd	5%	95%	n	mean	median	sd	5%	95%
Boom	2932	0.009	0.007	0.007	0.002	0.022	1873	0.011	0.009	0.008	0.003	0.025
Recession	336	0.014	0.011	0.009	0.005	0.035	329	0.015	0.013	0.008	0.002	0.030
Prime Grade	3268	0.009	0.008	0.007	0.002	0.024	2202	0.012	0.010	0.008	0.003	0.026
Boom	13346	0.010	0.008	0.007	0.003	0.022	4660	0.009	0.008	0.005	0.004	0.016
Recession	1605	0.017	0.014	0.011	0.007	0.037	802	0.019	0.016	0.011	0.007	0.039
Hight Grade	14951	0.010	0.008	0.008	0.003	0.025	5462	0.010	0.008	0.007	0.004	0.022
Boom	107411	0.015	0.012	0.011	0.005	0.033	48792	0.015	0.014	0.009	0.007	0.031
Recession	20979	0.034	0.028	0.024	0.013	0.070	11449	0.031	0.027	0.017	0.014	0.064
Medium Grade	128390	0.018	0.014	0.015	0.005	0.044	60241	0.018	0.015	0.012	0.007	0.042
Boom	123689	0.014	0.012	0.010	0.004	0.032	55325	0.015	0.013	0.008	0.006	0.030
Recession	22920	0.032	0.027	0.024	0.011	0.069	12580	0.030	0.026	0.017	0.012	0.062
Invt. Grade	146609	0.017	0.013	0.015	0.004	0.042	67905	0.018	0.015	0.012	0.006	0.040
Boom	33468	0.048	0.038	0.044	0.014	0.122	8825	0.045	0.036	0.041	0.016	0.109
Recession	9406	0.104	0.072	0.096	0.033	0.316	2121	0.108	0.071	0.109	0.030	0.319
Non-Invt. Grade	42874	0.060	0.043	0.064	0.015	0.159	10946	0.057	0.041	0.065	0.016	0.144

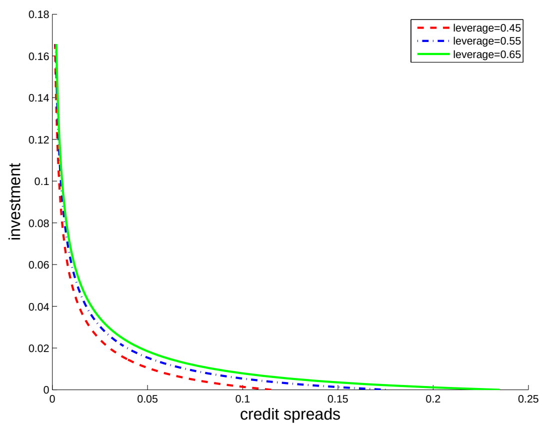
Table 1.3: Main Correlations

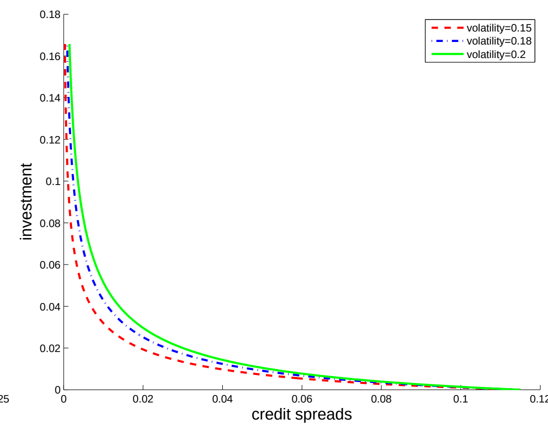
The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. CDS is the credit spreads and Int is the interaction term. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
I/K	1.000													
Q	0.201	1.000												
	(0.000)													
CDS	-0.112	-0.243	1.000											
	(0.000)	(0.000)												
Int	0.112	-0.006	0.142	1.000										
	(0.000)	(-0.611)	(0.000)											
Cash/K	0.181	0.206	-0.199	-0.010	1.000									
	(0.000)	(0.000)	(0.000)	(-0.393)										
Leverage	-0.053	-0.440	0.501	0.107	-0.248	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
Sales/K	0.214	0.011	-0.010	0.017	0.406	-0.059	1.000							
	(0.000)	(-0.376)	(-0.403)	(-0.154)	(0.000)	(0.000)								
log(size)	-0.007	0.074	-0.369	-0.145	0.060	-0.245	-0.040	1.000						
	(-0.555)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.001)							
Profit	0.237	0.243	-0.152	0.019	0.900	-0.210	0.552	0.022	1.000					
	(0.000)	(0.000)	(0.000)	(-0.114)	(0.000)	(0.000)	(0.000)	(-0.070)						
WW Index	-0.002	-0.087	0.366	0.104	-0.071	0.268	0.039	-0.717	-0.023	1.000				
	(-0.898)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.001)	(0.000)	(-0.052)					
SA Index	0.108	-0.043	0.392	0.113	-0.041	0.281	0.023	-0.706	0.007	0.567	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(-0.001)	(0.000)	(-0.054)	(0.000)	(-0.572)	(0.000)				
Rating	-0.008	-0.342	0.603	0.095	-0.179	0.547	0.013	-0.480	-0.142	0.458	0.458	1.000		
	(-0.479)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.286)	(0.000)	(0.000)	(0.000)	(0.000)			
Volatility	-0.022	-0.171	0.669	0.066	-0.156	0.400	-0.008	-0.293	-0.122	0.314	0.343	0.520	1.000	
	(-0.061)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(-0.500)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Recession	-0.104	-0.089	0.306	-0.031	-0.058	0.098	-0.020	0.024	-0.052	-0.010	0.007	0.047	0.198	1.000
	(0.000)	(0.000)	(0.000)	(-0.011)	(0.000)	(0.000)	(-0.088)	(-0.041)	(0.000)	(-0.417)	(-0.571)	(0.000)	(0.000)	

Table 1.4: Model Properties and Two-way sorts

In the upper panel plots, the benchmark parameters are h=0.5; r=0.055; β = 0.3; m=0.1; ψ = 0.45; c=0.08; δ = 0.15; σ = 0.2; μ = 0.002; θ = 1.05; K=20. In the lower panel tables, the firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. In the middle table, I sort firms into 5×5 portfolios by firm sales growth and credit spreads. In the bottom panel, I sort firms into 5×5 portfolios by firm volatility and credit spreads. Volatility is the annualized monthly stock return volatility from CRSP. For each portfolio I report the median of investment capital ratio.





	Credit Spreads						
Sales Growth	1(Low)	2	3	4	5(High)	Total	High-Low
1 (Low)	0.082	0.081	0.073	0.068	0.062	0.071	-0.020
2	0.079	0.075	0.080	0.080	0.076	0.078	-0.003
3	0.098	0.099	0.084	0.080	0.065	0.089	-0.033
4	0.110	0.106	0.098	0.103	0.094	0.104	-0.016
5 (High)	0.142	0.134	0.122	0.136	0.134	0.133	-0.008
Total	0.098	0.097	0.089	0.088	0.078	0.091	-0.020
High-Low	0.060	0.053	0.049	0.068	0.072	0.062	

	Credit Spreads						
Volatility	1(Low)	2	3	4	5(High)	Total	High-Low
1 (Low)	0.086	0.086	0.083	0.090	0.076	0.085	-0.010
2	0.095	0.091	0.088	0.083	0.095	0.090	0.000
3	0.117	0.098	0.087	0.083	0.084	0.094	-0.033
4	0.139	0.119	0.092	0.087	0.087	0.098	-0.052
5 (High)	0.170	0.156	0.130	0.106	0.072	0.090	-0.098
Total	0.098	0.097	0.089	0.088	0.077	0.091	-0.007
High-Low	0.084	0.070	0.047	0.016	-0.004	0.005	

Table 1.5: Overall

This table reports the regression results using overall sample. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. The first 4 columns are the estimates for the main measure. The last 4 columns are the estimates for an alternative measure. Details of the alternative measure are in Section 1.4.

	Main Measure				Alternative Measure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.265***		-0.201***	-0.205***	-0.184***		-0.136***	-0.133***
	(0.026)		(0.028)	(0.025)	(0.021)		(0.021)	(0.019)
log(Int)	0.150***		0.142***	0.127***	0.146***		0.142***	0.130***
	(0.027)		(0.029)	(0.028)	(0.028)		(0.030)	(0.030)
log(Q)		0.450***	0.316***	0.314***		0.455***	0.331***	0.325***
		(0.042)	(0.041)	(0.049)		(0.043)	(0.042)	(0.050)
Cash/K				0.147***				0.148***
				(0.037)				(0.037)
Leverage				0.294**				0.266**
				(0.127)				(0.129)
log(Size)				0.016				0.021
				(0.015)				(0.015)
Sales/K				0.021***				0.021***
				(0.003)				(0.003)
Volatility				0.040				0.023
				(0.074)				(0.068)
N	6914	6914	6914	6679	6758	6758	6758	6528
Adj. R^2	0.126	0.072	0.157	0.186	0.111	0.072	0.143	0.177

Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 1.6: Alternative Estimation Method

This table reports the regression results using overall sample. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. We use the firm fixed effect estimator with standard errors clustered at firm level. The within R^2 is reported.

	(1)	(2)	(3)	(4)
log(CDS)	-0.457***		-0.377***	-0.357***
	(0.020)		(0.021)	(0.021)
log(Int)	0.134***		0.161***	0.211***
	(0.026)		(0.026)	(0.025)
log(Q)		0.740***	0.520***	0.469***
		(0.050)	(0.045)	(0.044)
Cash/K				0.067*
				(0.037)
Leverage				-0.212
				(0.140)
log(Size)				0.154***
				(0.032)
Sales/K				0.043***
				(0.007)
Volatility				-0.018
				(0.016)
within R^2	0.210	0.125	0.266	0.315

Standard errors in parentheses
* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 1.7: Firm Characteristics and Elasticities: Sales Growth

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. I sort firms into 3 quantiles basing on their sales growth. The first 4 columns are the estimates for the first quantile (low growth). The last 4 columns are the estimates for the third quantile (high growth). In the bottom panel, I test the significance (Chow test) of the differences between coefficients in those two quantils for different specifications.

	Low Sales Growth				High Sales Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.292***		-0.270***	-0.257***	-0.231***		-0.139***	-0.207***
	(0.032)		(0.033)	(0.028)	(0.047)		(0.046)	(0.039)
log(Int)	0.149***		0.147***	0.141***	0.104***		0.077*	0.044
	(0.039)		(0.041)	(0.040)	(0.039)		(0.044)	(0.041)
log(Q)		0.311***	0.149**	0.092		0.530***	0.439***	0.421***
		(0.066)	(0.062)	(0.080)		(0.053)	(0.047)	(0.054)
Cash/K				0.337**				0.131***
				(0.156)				(0.048)
Leverage				0.279				0.240
				(0.182)				(0.203)
log(Size)				0.017				-0.004
				(0.024)				(0.025)
Sales/K				0.028*				0.011***
				(0.016)				(0.003)
Volatility				-0.027*				0.355*
				(0.016)				(0.198)
N	2307	2307	2307	2215	2285	2285	2285	2208
Adj. R^2	0.14	0.046	0.153	0.202	0.136	0.119	0.193	0.23

Standard errors in parentheses $^{*}\ p < 0.10,^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

	—(5)—-—(1)—			—(7)—-—(3)—			—(8)—-—(4)—		
	difference	χ^2	p-value	difference	χ^2	p-value	difference	χ^2	p-value
CDS	-0.061**	5.110	0.024	-0.131***	21.850	0.000	-0.050	2.300	0.130
Int	-0.045	1.960	0.161	-0.070**	4.790	0.029	-0.097***	9.440	0.002

$^{*}\ p < 0.10,^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

Table 1.8: Firm Characteristics and Elasticities: Volatility

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. I sort firms into 3 quantiles basing on their volatility. The first 4 columns are the estimates for the first quantile (low volatility). The last 4 columns are the estimates for the third quantile (high volatility). In the bottom panel, I test the significance (Chow test) of the differences between coefficients in those two quantils for different specifications.

	Low Volatility				High Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.135***		-0.095**	-0.177***	-0.454***		-0.352***	-0.315***
	(0.043)		(0.042)	(0.042)	(0.032)		(0.036)	(0.031)
log(Int)	0.109***		0.105***	0.100***	0.201***		0.193***	0.176***
	(0.031)		(0.033)	(0.033)	(0.056)		(0.058)	(0.054)
log(Q)		0.223***	0.177***	0.135**		0.750***	0.495***	0.528***
		(0.053)	(0.053)	(0.063)		(0.066)	(0.067)	(0.078)
Cash/K				0.240**				0.130**
				(0.122)				(0.056)
Leverage				0.321				0.253
				(0.197)				(0.185)
log(Size)				0.022				0.024
				(0.019)				(0.023)
Sales/K				0.023***				0.019***
				(0.006)				(0.005)
Volatility				0.574***				-0.025
				(0.160)				(0.032)
N	2234	2234	2234	2229	2219	2219	2219	2187
Adj. R^2	0.063	0.018	0.074	0.107	0.157	0.099	0.192	0.23

Standard errors in parentheses * $p < 0.10,^{**}$ $p < 0.05$, *** $p < 0.01$

	—(5)—-—(1)—			—(7)—-—(3)—			—(8)—-—(4)—		
	difference	χ^2	p-value	difference	χ^2	p-value	difference	χ^2	p-value
CDS	0.319***	125.510	0.000	0.257***	71.770	0.000	0.138***	16.420	0.000
Int	0.092**	5.690	0.017	0.088**	5.300	0.021	0.076**	4.340	0.037

* $p < 0.10,^{**}$ $p < 0.05$, *** $p < 0.01$

Table 1.9: Bond Characteristics and Elasticities: Maturity

This table reports the regression results using different bonds. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. Define long term as the term to maturity above 15 years, medium term as between 7 and 15 years, and short term as below 7 years. The first 4 columns are the estimates for short and medium term bonds only. The last 4 columns are the estimates for the long term bonds only. In the bottom panel, I test the significance (Chow test) of the differences between coefficients in those two quantils for different specifications.

	Short and Medium Term				Long Term			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.248***		-0.176***	-0.186***	-0.311***		-0.253***	-0.284***
	(0.028)		(0.029)	(0.027)	(0.029)		(0.034)	(0.028)
log(Int)	0.174***		0.182***	0.179***	-0.045		0.062	0.102
	(0.034)		(0.038)	(0.037)	(0.075)		(0.078)	(0.083)
log(Q)		0.466***	0.347***	0.340***		0.370***	0.248***	0.218***
		(0.042)	(0.042)	(0.051)		(0.059)	(0.067)	(0.071)
Cash/K				0.147***				0.191**
				(0.038)				(0.095)
Leverage				0.273**				0.156
				(0.129)				(0.246)
log(Size)				0.007				0.043*
				(0.016)				(0.024)
Sales/K				0.022***				0.046***
				(0.003)				(0.010)
Volatility				0.046				0.314*
				(0.077)				(0.167)
N	6530	6530	6530	6310	2616	2616	2616	2563
Adj. R^2	0.12	0.076	0.152	0.181	0.135	0.069	0.167	0.197

Standard errors in parentheses $^{*}\ p < 0.10, ^{**}\ p < 0.05, ^{***}\ p < 0.01$

	—(5)—-—(1)—			—(7)—-—(3)—			—(8)—-—(4)—		
	difference	χ^2	p-value	difference	χ^2	p-value	difference	χ^2	p-value
CDS	0.063***	9.610	0.002	0.077***	12.590	0.000	0.098***	13.520	0.000

$^{*}\ p < 0.10, ^{**}\ p < 0.05, ^{***}\ p < 0.01$

Table 1.10: Robustness: Different Time Periods

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. Definition of booms and recessions follows NBER. It is one if it is in recession, and zero otherwise. The first 4 columns are the estimates using sample in booms only. The last 4 columns are the estimates using sample in recessions only.

	Booms				Recessions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.244***		-0.177***	-0.195***	-0.289***		-0.230***	-0.218***
	(0.035)		(0.037)	(0.032)	(0.033)		(0.033)	(0.028)
log(Int)	0.163***		0.153***	0.137***	0.112***		0.110***	0.096**
	(0.028)		(0.031)	(0.031)	(0.028)		(0.033)	(0.038)
log(Q)		0.428***	0.322***	0.331***		0.443***	0.298***	0.252***
		(0.048)	(0.046)	(0.056)		(0.042)	(0.041)	(0.045)
Cash/K				0.156***				0.135***
				(0.056)				(0.029)
Leverage				0.333**				0.141
				(0.150)				(0.174)
log(Size)				0.019				0.014
				(0.017)				(0.020)
Sales/K				0.021***				0.020***
				(0.004)				(0.006)
Volatility				0.131				-0.000
				(0.167)				(0.071)
N	4996	4996	4996	4833	1918	1918	1918	1846
Adj. R^2	0.113	0.06	0.145	0.169	0.131	0.061	0.155	0.186

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Robustness: Bond Ratings

This table reports the regression results using different bonds. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. Define investment grade as Aaa to Baa3, and non-investment grade as below Baa3. The first 4 columns are the estimates using investment grade bonds only. The last 4 columns are the estimates using non-investment grade bonds only.

	Invt. Grade				Non-Invt. Grade			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.286***		-0.223***	-0.280***	-0.502***		-0.411***	-0.352***
	(0.029)		(0.031)	(0.026)	(0.063)		(0.063)	(0.059)
log(Int)	0.122***		0.123***	0.111***	0.236***		0.190***	0.164**
	(0.031)		(0.033)	(0.033)	(0.073)		(0.072)	(0.065)
log(Q)		0.360***	0.269***	0.237***		0.739***	0.518***	0.520***
		(0.046)	(0.045)	(0.049)		(0.089)	(0.092)	(0.099)
Cash/K				0.185***				0.139***
				(0.047)				(0.043)
Leverage				0.222				0.194
				(0.188)				(0.204)
log(Size)				0.030*				0.019
				(0.017)				(0.030)
Sales/K				0.020***				0.019***
				(0.004)				(0.004)
Volatility				0.425***				-0.003
				(0.151)				(0.038)
N	4796	4796	4796	4683	2002	2002	2002	1916
Adj. R^2	0.105	0.067	0.142	0.175	0.11	0.081	0.139	0.177

Standard errors in parentheses

* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 1.12: Robustness: Liquidity

This table reports the regression results using different bonds. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. Following Bao et al. (2011), I construct an individual bond liquidity measure. Let $p_t = ln(P_t)$ where P_t is the bond price. Then the liquidity $\gamma = -Cov\left[(p_t - p_{t-1}), (p_{t+1} - p_t)\right]$. The higher the γ, the more illiquid the bond is. I sort bonds into 3 quantiles basing on γ. The first 4 columns are the estimates using low illiquid bonds only. The last 4 columns are the estimates using high illiquid grade bonds only.

	Low Illiquid Bonds				High Illiquid Bonds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.254***		-0.190***	-0.200***	-0.306***		-0.245***	-0.244***
	(0.030)		(0.033)	(0.030)	(0.028)		(0.029)	(0.029)
log(Int)	0.083***		0.073**	0.052*	0.133***		0.137***	0.123***
	(0.030)		(0.029)	(0.028)	(0.032)		(0.031)	(0.031)
log(Q)		0.454***	0.302***	0.277***		0.471***	0.334***	0.309***
		(0.051)	(0.050)	(0.059)		(0.055)	(0.056)	(0.060)
Cash/K				0.146***				0.140***
				(0.039)				(0.038)
Leverage				0.152				0.086
				(0.171)				(0.166)
log(Size)				-0.005				0.025
				(0.020)				(0.021)
Sales/K				0.026***				0.025***
				(0.005)				(0.004)
Volatility				0.035				0.116
				(0.087)				(0.132)
N	3941	3941	3941	3830	3671	3671	3671	3557
Adj. R^2	0.114	0.072	0.145	0.179	0.13	0.072	0.16	0.189

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.13: Option Value

This table reports the regression results using different proxies for option value. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. In the upper panel, the option value proxy is Tobin's Q. In the lower panel, the option value proxy is firm R&D. Control variables include firm size, leverage, sales, and volatility.

	Tobin's Q: Low Option Value				Tobin's Q: High Option Value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.290***		-0.247***	-0.242***	-0.166***		-0.129***	-0.232***
	(0.035)		(0.038)	(0.038)	(0.042)		(0.043)	(0.041)
log(Int)	0.120***		0.123***	0.087*	0.166***		0.163***	0.163***
	(0.044)		(0.046)	(0.048)	(0.036)		(0.039)	(0.036)
log(Q)		1.058***	0.624***	0.469***		0.385***	0.327***	0.210***
		(0.156)	(0.143)	(0.155)		(0.072)	(0.071)	(0.071)
Cash/K				0.118***				0.094
				(0.045)				(0.082)
Control	N	N	N	Y	N	N	N	Y
N	2303	2303	2303	2189	2279	2279	2279	2232
Adj. R^2	0.111	0.045	0.118	0.143	0.079	0.036	0.098	0.125

	R&D: Low Option Value				R&D: High Option Value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.396***		-0.276***	-0.298***	-0.224***		-0.176***	-0.271***
	(0.048)		(0.043)	(0.046)	(0.043)		(0.049)	(0.051)
log(Int)	0.150**		0.132**	0.112**	0.200***		0.198***	0.173***
	(0.061)		(0.051)	(0.052)	(0.042)		(0.042)	(0.044)
log(Q)		0.886***	0.706***	0.635***		0.282***	0.192***	0.189***
		(0.081)	(0.084)	(0.098)		(0.064)	(0.070)	(0.071)
Cash/K				0.241				0.345***
				(0.263)				(0.098)
Control	N	N	N	Y	N	N	N	Y
N	1275	1275	1275	1199	1255	1255	1255	1250
Adj. R^2	0.151	0.129	0.209	0.241	0.149	0.064	0.186	0.22

Standard errors in parentheses
* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 1.14: Sentiment and Investment

This table reports the regression results in high and low sentiment periods. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. The first (last) 4 columns are the estimates in low (high) periods.

	Low Sentiment				High Sentiment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.286***		-0.225***	-0.213***	-0.242***		-0.176***	-0.244***
	(0.022)		(0.023)	(0.023)	(0.050)		(0.051)	(0.054)
log(Int)	0.146***		0.134***	0.114***	0.154***		0.155***	0.146***
	(0.030)		(0.033)	(0.031)	(0.034)		(0.036)	(0.037)
log(Q)		0.495***	0.310***	0.282***		0.391***	0.315***	0.273***
		(0.039)	(0.040)	(0.055)		(0.051)	(0.047)	(0.058)
Cash/K				0.173***				0.167***
				(0.063)				(0.037)
Leverage				0.176				0.119
				(0.152)				(0.169)
log(Size)				0.010				0.024
				(0.014)				(0.017)
Sales/K				0.019***				0.022***
				(0.004)				(0.004)
Volatility				-0.032				0.448***
				(0.023)				(0.116)
N	3076	3076	3076	2979	3374	3374	3374	3259
Adj. R^2	0.155	0.082	0.181	0.21	0.083	0.045	0.112	0.148

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.15: Financial Constraint I

In the upper panel, all firms are sorted into 5 portfolios by WW or SA financial constraint index. The summary statistics of credit spreads (CDS) and Tobin's Q are reported for each portfolio. "1" indicates the least constrained group and "5" is the most constrained group. In the lower panel, regression results are reported. The dependent variable is credit spreads (Tobin's Q) in the first (last) 3 columns.

	CDS		Tobin's Q			CDS		Tobin's Q	
WW	mean	median	mean	median	SA	mean	median	mean	median
1	0.016	0.012	1.822	1.492	1	0.020	0.014	1.687	1.402
2	0.021	0.015	1.722	1.472	2	0.025	0.018	1.776	1.557
3	0.025	0.018	1.694	1.475	3	0.028	0.019	1.656	1.422
4	0.034	0.024	1.569	1.359	4	0.029	0.021	1.679	1.436
5	0.053	0.039	1.489	1.268	5	0.049	0.036	1.551	1.311
1= Least Constrained; 5=Most Constrained									

	CDS			Tobin's Q		
WW	6.985*		4.708	-1.488*		-1.841
	(3.954)		(3.362)	(0.884)		(1.155)
WW^2	1.905		0.331	-0.855		-1.135
	(4.747)		(3.877)	(1.124)		(1.385)
SA		0.528***	0.192**		-0.043	0.036
		(0.063)	(0.092)		(0.053)	(0.061)
SA^2		0.028	0.017		0.001	0.007
		(0.023)	(0.027)		(0.018)	(0.019)
N	6882	6895	6882	6882	6895	6882
Adj. R^2	0.260	0.179	0.269	0.020	0.006	0.020

Standard errors in parentheses
* p¡0.1, ** p¡0.05, *** p¡0.01

Table 1.16: Financial Constraint II

This table reports the summary statistics of sample firms and firms out of sample. The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. I sort firms into 5 quantiles using WW and SA indices. "1" indicates the least constrained group and "5" is the most constrained group.

	Sample		COMPUSTAT Firm									
WW Index			Least Constrained (1)		(2)		(3)		(4)		Most Constrained (5)	
	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median
log(Size)	8.555	8.574	7.902	7.868	6.262	6.217	5.279	5.290	4.349	4.387	3.290	3.227
Age	32.388	35.000	19.500	16.000	16.801	14.000	13.152	10.000	11.453	9.000	10.563	8.000
Firm Rating	11.605	11.000	11.538	11.000	14.895	15.000	16.236	16.000	17.210	17.000	17.994	17.000
Payout	0.246	0.162	0.212	0.137	0.194	0.095	0.142	0.005	0.093	0.000	0.021	0.000
Cash/K	0.198	0.152	0.149	0.161	0.295	0.195	0.275	0.196	0.090	0.149	-0.778	-0.062
Profitability	0.336	0.235	0.298	0.236	0.483	0.292	0.489	0.291	0.293	0.215	-0.506	-0.006
Book Leverage	0.320	0.293	0.265	0.247	0.249	0.225	0.234	0.194	0.214	0.150	0.238	0.167
Equity Issuance	0.012	0.003	0.031	0.002	0.030	0.003	0.038	0.003	0.045	0.003	0.087	0.003
Tangibility	0.437	0.456	0.487	0.507	0.514	0.532	0.534	0.544	0.560	0.559	0.577	0.570

	Sample		COMPUSTAT Firm									
SA Index			Least Constrained (1)		(2)		(3)		(4)		Most Constrained (5)	
	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median
log(Size)	8.555	8.574	8.058	7.923	6.325	6.287	5.192	5.188	4.186	4.179	3.060	3.035
Age	32.388	35.000	24.816	25.000	16.300	14.000	12.404	10.000	10.292	8.000	8.492	7.000
Firm Rating	11.605	11.000	11.952	12.000	15.297	15.000	16.497	16.000	17.143	16.000	15.821	16.000
Payout	0.246	0.162	0.205	0.130	0.167	0.059	0.128	0.000	0.090	0.000	0.046	0.000
Cash/K	0.198	0.152	0.189	0.150	0.216	0.172	0.162	0.175	-0.128	0.132	-0.716	-0.003
Profitability	0.336	0.235	0.335	0.231	0.424	0.263	0.388	0.260	0.092	0.190	-0.490	0.023
Book Leverage	0.320	0.293	0.279	0.258	0.274	0.250	0.238	0.193	0.199	0.125	0.200	0.121
Equity Issuance	0.012	0.003	0.014	0.002	0.025	0.003	0.041	0.003	0.064	0.004	0.107	0.005
Tangibility	0.437	0.456	0.480	0.503	0.506	0.526	0.541	0.547	0.575	0.568	0.582	0.576

Table 1.17: WW Index

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. I sort firms into 3 quantiles basing on the index. The first 4 columns are the estimates for the first quantile (least constrained). The last 4 columns are the estimates for the third quantile (most constrained). In the bottom panel, I report the summary statistics of firm sales growth and volatility of those three quantiles.

	Less Constrained				More Constrained			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.206***		-0.120**	-0.224***	-0.343***		-0.275***	-0.245***
	(0.042)		(0.047)	(0.043)	(0.040)		(0.039)	(0.034)
log(Int)	0.132***		0.128***	0.111***	0.182***		0.174***	0.154***
	(0.039)		(0.040)	(0.039)	(0.064)		(0.064)	(0.058)
log(Q)		0.373***	0.307***	0.225***		0.576***	0.389***	0.406***
		(0.059)	(0.066)	(0.071)		(0.076)	(0.066)	(0.075)
Cash/K				0.136**				0.070
				(0.063)				(0.058)
Leverage				-0.016				0.314*
				(0.241)				(0.188)
log(Size)				-0.021				0.079***
				(0.047)				(0.028)
Sales/K				0.020***				0.023***
				(0.005)				(0.006)
Volatility				0.860***				-0.031
				(0.165)				(0.030)
N	2303	2303	2303	2226	2281	2281	2281	2188
Adj. R^2	0.113	0.06	0.145	0.171	0.114	0.083	0.147	0.175

Standard errors in parentheses $^{*}\ p < 0.10,^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

		Sales Growth		Volatility	
WW Index		mean	median	mean	median
less constrained	1	0.077	0.041	0.325	0.289
	2	0.054	0.038	0.363	0.318
more constrained	3	0.030	0.022	0.478	0.396

Table 1.18: SA Index

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. I sort firms into 3 quantiles basing on the index. The first 4 columns are the estimates for the first quantile (least constrained). The last 4 columns are the estimates for the third quantile (most constrained). In the bottom panel, I report the summary statistics of firm sales growth and volatility of those three quantiles.

	Less Constrained				More Constrained			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.272***		-0.222***	-0.287***	-0.313***		-0.233***	-0.206***
	(0.031)		(0.036)	(0.033)	(0.038)		(0.038)	(0.036)
log(Int)	0.129***		0.134***	0.131***	0.223***		0.218***	0.194***
	(0.041)		(0.042)	(0.044)	(0.059)		(0.060)	(0.050)
log(Q)		0.329***	0.184***	0.159**		0.598***	0.465***	0.480***
		(0.064)	(0.069)	(0.068)		(0.069)	(0.068)	(0.080)
Cash/K				0.203***				0.097
				(0.069)				(0.073)
Leverage				0.117				0.370**
				(0.250)				(0.176)
log(Size)				0.002				0.058**
				(0.036)				(0.026)
Sales/K				0.022***				0.024***
				(0.007)				(0.005)
Volatility				0.510***				0.009
				(0.159)				(0.083)
N	2447	2447	2447	2410	2261	2261	2261	2136
Adj. R^2	0.148	0.042	0.167	0.196	0.084	0.077	0.119	0.135

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

		Sales Growth		Volatility	
SA Index		mean	median	mean	median
less constrained	1	0.041	0.027	0.334	0.295
	2	0.054	0.038	0.376	0.316
more constrained	3	0.067	0.039	0.462	0.390

Table 1.19: Debt Overhang, Credit Spreads, and Tobin's Q

In the upper panel, the first (last) 3 columns report the regression results when credit spreads (Tobin's Q) are the dependent variable. The lower panel reports the regression results from firms with more and less debt overhang. CDS is the credit spreads and Int is the interaction term.

	CDS			Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Default	-0.078***		-0.066***	0.034***		0.037***
	(0.008)		(0.009)	(0.003)		(0.004)
Book Leverage		1.583***	0.759***		-0.240***	0.226**
		(0.131)	(0.128)		(0.088)	(0.106)
N	6635	6895	6635	6635	6895	6635
Adj. R^2	0.237	0.114	0.258	0.151	0.009	0.158

	Less Overhang			More Overhang		
	(1)	(2)	(3)	(4)	(5)	(6)
	Default Prob.	Leverage	Lev × D.Prob.	Default Prob.	Leverage	Lev × D.Prob.
log(CDS)	-0.055	-0.174***	-0.049	-0.283***	-0.274***	-0.302***
	(0.046)	(0.041)	(0.047)	(0.039)	(0.041)	(0.041)
log(Int)	0.168***	0.114***	0.148***	0.294***	0.132**	0.251***
	(0.040)	(0.036)	(0.039)	(0.050)	(0.059)	(0.057)
N	2303	2299	2303	2270	2274	2273
Adj. R^2	0.033	0.039	0.026	0.059	0.056	0.060

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.20: Impact of Debt Overhang

This table reports the regression results using different samples. The independent variable is investment capital ratio. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions. I sort firms into 3 quantiles basing on the debt overhang proxy. The first 4 columns are the estimates for the first quantile (less overhang). The last 4 columns are the estimates for the third quantile (more overhang).

	Less Overhang				More Overhang			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(CDS)	-0.138***		-0.071*	-0.091**	-0.404***		-0.350***	-0.330***
	(0.038)		(0.037)	(0.036)	(0.044)		(0.045)	(0.038)
log(Int)	0.144***		0.132***	0.128***	0.220***		0.199***	0.184***
	(0.037)		(0.037)	(0.038)	(0.060)		(0.061)	(0.055)
log(Q)		0.342***	0.303***	0.235***		0.577***	0.415***	0.417***
		(0.049)	(0.050)	(0.061)		(0.083)	(0.084)	(0.097)
Cash/K				0.156*				0.123***
				(0.094)				(0.045)
Leverage				-0.274				0.143
				(0.277)				(0.209)
log(Size)				0.033*				0.009
				(0.020)				(0.026)
Sales/K				0.012***				0.025***
				(0.004)				(0.005)
Volatility				0.052				0.032
				(0.091)				(0.082)
N	2303	2303	2303	2246	2279	2279	2279	2179
Adj. R^2	0.08	0.069	0.127	0.17	0.135	0.073	0.163	0.209

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.21: Distance to Default and Credit Spreads

This table reports the regression results. The independent variable is credit spreads. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. The monthly data range from 1980 to 2011. DD is the distance to default, and its calculation is in Appendix A.2. Following Bao et al. (2011), I construct an individual bond liquidity measure. Let $p_t = ln(P_t)$ where P_t is the bond price. Then the liquidity $\gamma = -Cov\left[(p_t - p_{t-1}),\ (p_{t+1} - p_t)\right]$. The higher the γ, the more illiquid the bond is. Volatility is the annualized monthly stock return volatility from CRSP. The risk free rate is the yield of the pseudo security (see Section 1.3). Bond rating and issuer industry effect are added in column (5) and (10)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DD	-0.101***		-0.099***	-0.092***	-0.060***	-0.053***		-0.052***	-0.056***	-0.039***
	(0.004)		(0.004)	(0.003)	(0.004)	(0.003)		(0.003)	(0.002)	(0.003)
Liquidity		9.316***	3.953**	5.249***	1.728*		3.336	1.175	2.688*	0.381
		(2.820)	(1.798)	(1.749)	(0.939)		(2.501)	(1.593)	(1.520)	(0.975)
Duration				-0.020***	-0.020***				-0.016**	-0.023***
				(0.007)	(0.006)				(0.007)	(0.006)
Convexity				-0.002***	-0.000				-0.001***	0.000
				(0.000)	(0.000)				(0.000)	(0.000)
log(Maturity)				0.418***	0.248***				0.346***	0.229***
				(0.037)	(0.031)				(0.031)	(0.029)
log(Age)				-0.035***	-0.011				-0.021***	-0.006
				(0.008)	(0.007)				(0.007)	(0.007)
Risk Free Rate				-0.140***	-0.112***				-0.112***	-0.095***
				(0.009)	(0.010)				(0.008)	(0.010)
Volatility						1.717***	1.525**	1.734***	1.357***	0.862***
						(0.089)	(0.611)	(0.097)	(0.083)	(0.087)
Rating & Ind.	No	No	No	No	Yes	No	No	No	No	Yes
N	220542	276498	207731	204286	169913	220542	210070	207731	204286	169913
Adj. R^2	0.3592	0.0024	0.3545	0.4712	0.6577	0.4607	0.2418	0.4561	0.5295	0.6759

Standard errors in parentheses
* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 1.22: Distance to Default and Investment

This table reports the regression results using overall sample. The independent variable is investment capital ratio. DD is the distance to default, and its calculation is in Appendix A.2. CDS is the credit spreads and Int is the interaction term. Q is the market to book ratio. Cash/K is the cash flow. Leverage is the market leverage. Size is the total book value of assets (in 2004 dollars). Volatility is the annualized monthly stock return volatility from CRSP. The details of variable definition are in Appendix A.5. The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We drop the firms with total asset below 10 million dollars (in year 2004 dollars). We also drop the firms with missing values in investment or capital stock, and firms with negative market to book ratio. The credit market information comes from different sources, and the detail information of database, data cleaning, and variable construction is in Section 1.3. Investment, credit spreads, interaction term and Q are in logarithm. Standard errors are clustered at both firm and time dimensions.

	(1)	(2)	(3)	(4)	(5)
DD	0.032***	0.012***	0.016***	-0.001	-0.002
	(0.006)	(0.004)	(0.006)	(0.004)	(0.004)
log(CDS)		-0.229***		-0.211***	-0.217***
		(0.029)		(0.030)	(0.027)
log(Int)		0.143***		0.134***	0.123***
		(0.027)		(0.029)	(0.029)
log(Q)			0.348***	0.305***	0.314***
			(0.049)	(0.046)	(0.050)
Cash/K					0.151***
					(0.036)
Leverage					0.280**
					(0.133)
log(Size)					0.016
					(0.015)
Sales/K					0.021***
					(0.003)
Volatility					0.032
					(0.069)
N	6623	6623	6623	6623	6571
Adj. R^2	0.048	0.131	0.083	0.154	0.181

Standard errors in parentheses
* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Chapter 2

Investment and the Weighted Average Cost of Capital

In this paper we study the impact of the weighted average cost of capital (WACC) on corporate investment. For decades business students have been taught to evaluate corporate investments by projecting cash flows and discounting them using the WACC. The WACC is composed of cost of equity and the cost of debt, these are weighted to reflect corporate leverage and debt is adjusted for corporate tax.[1] In surveys such as Graham and Harvey (2001) and AFP (2011) many financial managers say that they do this. So it might have an important impact.

The corporate investment model of Andrew and Blanchard (1986) is used as an organizing framework. WACC enters the model through the discount factor so that, when it is high the expected value of the future marginal benefit is reduced

[1] To define the textbook WACC, let E denote the value of equity, D denotes the value of debt, $V = D + E$ is the total value of the firm, r_E is the equity cost of capital, r_D is the debt cost of capital, τ_c is the corporate tax rate, the weighted average cost of capital is, $WACC = \frac{E}{V} r_E + \frac{D}{V} r_D (1 - \tau_c)$. Myers (1974) already referred to the WACC as 'the textbook formula.' The approach is taught by most modern corporate finance textbooks such as Benninga (2008), Berk and DeMarzo (2011), Brealey et al. (2006), Damodaran (2002), Graham et al. (2010), Koller et al. (2010), and Ross et al. (2008).

which reduces the incentive to invest now. Empirically, a high cost of debt has a negative impact on investment. High leverage also has a negative impact on investment. The tax impact is not well estimated. Both the sign of the tax effect and the statistical significance are sensitive to the choice of proxy and to the time period.

A challenging aspect is the impact of the cost of equity. Using the CAPM, the Fama and French (1993) model (denoted $FF3$), or the Carhart (1997) model (denoted Car), a high cost of equity is generally associated with high investment. This is contrary to the predictions from the Andrew and Blanchard (1986) model. The question is, why?

One possibility is that we have incorrectly left out q. In the Andrew and Blanchard (1986) model Tobin's q does not belong in the investment equation because the more fundamental determinants are entered directly. However, in the empirical literature q is often used in investment regressions along with a variety of other regressors despite what theory says to do.[2] For comparability with such studies we also report regressions that include q along with the components of WACC. The impact of the cost of equity is not sensitive to the inclusion or omission of q. This does not resolve the problem.

A second possible reason is that the components of WACC are really determined at a deeper level by other factors. So we use dynamic factor analysis methods similar to Bernanke et al. (2005), Ludvigson and Ng (2009), and Stock and Watson (2012), in order to study the impact of macro conditions on the WAC-C. Empirically three macro factors are significant. The first factor reflects interest rates (i.e. cost of debt). The second factor reflects stock market performance (i.e. cost of equity). The third factor reflects exchange rates. These these factors seem

[2]Finding that these other variables matter is often interpreted as a rejection of theory. Others interpret it as a rejection of the empirical proxy for q.

sensible. But when used within the Andrew and Blanchard (1986) model they do not resolve the puzzling impact of the cost of equity on investment.

A third possibility is that the Andrew and Blanchard (1986) model is misspecified. The model does not fully endogenize the comovements of the cost of equity, cash flow, and investment. Accordingly we studied whether the model in Zhang (2005) has a different predicted linkage between the cost of equity and corporate investment. Using that model we simulate a panel of 1000 firms for 800 periods. We run investment regressions on the simulated data. But, as in Andrew and Blanchard (1986), the cost of equity has a negative impact on investment in the simulated data.

A fourth possibility is that actual stock returns are not a good reflection of expected stock returns. Perhaps with a better measure of expected stock returns we might find the theoretically predicted negative sign on equity. This motivates consideration of an approach known as the 'implied cost of equity capital', or 'implied cost of capital' as in Gebhardt et al. (2001) and Chava and Purnanandam (2010). There are alternative versions of the implied cost approach and we have explored a number of them. Consistent results are obtained across versions. Specifically, high implied cost of equity capital is associated with reduced corporate investment. This is consistent with the investment predictions in both Andrew and Blanchard (1986) and Zhang (2005).

The rest of the introduction discusses the prior literature. Section 2.2 derives the model of corporate investment. The data is described in section 2.3. Basic investment regression results are reported in 2.4. Section 2.5 considers the predicted impact of the cost of equity in the Zhang (2005) model. In section 2.6 a dynamic factor approach is taken to allow for a wide range of potential macroeconomic factors on WACC. The cost of equity capital according the the implied cost of capital approach is studied in section 2.7. The conclusion is section 2.8.

2.1 Prior Literature

To the best of our knowledge this is the first paper to systematically study the impact of the WACC on corporate investment. There are surprisingly few studies of the WACC altogether.

The idea that WACC matters for corporate investment dominates the finance textbooks. But there is surprisingly little direct evidence either for or against the idea. There is some support from a small number of studies of specialized settings. Our paper contributes broad-based evidence. The study by Kaplan and Ruback (1995) is a study a sample of high leverage transactions between 1983 and 1989 for which they have cost of capital and expected cash flow information. Gilson et al. (2000) is a study of a sample of firms in bankruptcy reorganization. In both of these studies they have published cash flow forecasts. In both studies the discounted cash flow analysis performs rather well. These studies do not focus on the components of the WACC, and they leave unclear how broadly applicable the approach might be.

There are many studies of stock returns. But these are not generally related to corporate investment. Noteworthy exceptions are papers in the investment based asset pricing literature such as Liu et al. (2009) and the studies discussed by Lin and Zhang (2013). These papers provide a motivation for attention to investment when studying historical stock returns. Our evidence suggests that the historical stock returns may not be a good reflection of expected stock returns.

The disconnect between historical and expected stock returns is also found in Chava and Purnanandam (2010). They study the empirical linkage between default risk and stock returns. In contrast our paper studies the linkage between corporate investment and stock returns. Their approach to resolving the seemingly anomalous evidence is quite similar to ours, despite the rather different settings. Both their paper, and ours make use of an implied cost of equity capital approach to model expected stock returns.[3]

We are not the first to ask about the impact of debt markets on corporate investment. Philippon (2009) links bond prices to unobservable marginal q. To do this he calibrates a dynamic investment model. He finds that the bond price implied q performs much better than the traditional equity based q using aggregate investment data. Thus he uses the bond market as an alternative source to infer q.

In contrast to Philippon (2009) we regard the bond market and the equity market as two sources of financing that need to be weighted, rather than alternative data source to use to develop a proxy for q. Philippon (2009) studies the cost of debt only. This distinction proves to be important since we show that the effect of expected return of debt on investment is not simply a better proxy for the expected return on equity. Conceptually this emerges clearly from the analysis of Liu et al. (2009). Our evidence can be seen as providing an explanation for why Philippon (2009) obtained better empirical results using the bond market. At the same time we show how to the empirically important, cost of equity.

From a different point of view Gilchrist and Zakrajsek (2007) examines the empirical impact of cost of debt on firm investment, using firm credit spreads as a proxy. They run the investment regressions and find that investment is negatively

[3]The classical imputation method is the Gordon growth model, as taught in textbooks such as Benninga (2008). An increasingly popular version is based on residual income accounting as proposed by Gebhardt et al. (2001) (GLS) and further studied by Pastor et al. (2008), Nekrasov and Shroff (2009), Hou et al. (2011), Lee et al. (2010) and Lewellen (2010).

related with the cost of debt. We also find this effect. Because we are studying the WACC, we were obliged to consider issues that do not arise in Gilchrist and Zakrajsek (2007) or Philippon (2009). In particular we found that the cost of equity is very important to computing the WACC, while Philippon (2009) and Gilchrist and Zakrajsek (2007) do not consider the impact of cost of equity on investment, which is a major focus of our paper.

As far as we know we are the first to use of factor augmented vector autoregressions for our purposes. Gilchrist et al. (2009) study both the impact of shocks to the stock market and to the bond market using factor-augmented vector autoregressions. However, they study the effects on employment and industrial production rather than studying corporate investment. Furthermore they do not attempt to tie their results back to the WACC. The evidence in Gilchrist et al. (2009) is similar in spirit to Philippon (2009), in that they find that credit market data seems to have better predictive ability than does the equity market data for subsequent macroeconomic performance. While these studies are somewhat related to what we do, they do not directly address the connection between the cost of equity and corporate investment.

Carlson et al. (2004) considers the importance of fixed operating costs. They model the following idea. Suppose that a firm has an increase in product demand then the value of equity rises relative to book value. Assume that fixed operating costs are proportional to capital. So leverage falls and the firms is safer. Because the firm is safer the equilibrium expected return must decline. They use this to account for the size and market to book factors that are elements of the popular Fama-French and Carhart models.[4]

[4] Carlson et al. (2006) use corporate investment to help understand the stock return patterns around seasoned equity offerings (SEOs). They view the firm as being compose of assets in place and growth options. Prior to an SEO the growth option is drifting 'into the money.' At

2.2 Corporate Investment Model

The model follows Andrew and Blanchard (1986). Notation: $V(\cdot,\cdot)$ is the value of the firm, K_t is capital stock, I_t is investment, δ is the rate at which capital depreciates ($0 < \delta < 1$), r_t is the discount rate (or, as observed by Andrew and Blanchard (1986), the WACC), $\pi(\cdot,\cdot)$ is the flow of revenue in a period, $c(\cdot,\cdot)$ is the capital adjustment cost function, a_t is the production function shock, $\phi > 0$ is a parameter in the adjustment cost function, Ω_t is the information set available when making period t decisions. We suppress the firm subscript i here. The adjustment cost is linear homogenous in I_t and K_t , $c(I_t, K_t) = I_t + \frac{\phi}{2}(\frac{I_t}{K_t})^2 K_t$. Capital accumulation is given by, $K_{t+1} = K_t(1-\delta) + I_t$.

The firm chooses investment to maximize the expected present value of the firm,

$$V(a_t, K_t) = E\left\{\sum_{j=0}^{\infty} \frac{\pi(a_{t+j}, K_{t+j}) - c(I_{t+j}, K_{t+j})}{\Pi_{s=1}^{j}(1 + r_{t+s})}|\Omega_t\right\} \tag{2.1}$$

Using subscripts to denote derivatives, the first order condition is, $c_I(I_t, K_t) = q_t$.

Due to the quadratic adjustment cost function, the first order condition can be expressed as,

$$\frac{I_t}{K_t} = -\frac{1}{\phi} + \frac{1}{\phi}q_t$$

where,

$$q_t = E\left\{\sum_{j=1}^{\infty} \frac{(1-\delta)^{j-1}[\pi_K(a_{t+j}, K_{t+j}) - c_K(I_{t+j}, K_{t+j})]}{\Pi_{s=1}^{j}(1 + r_{t+s})}|\Omega_t\right\}. \tag{2.2}$$

As usual, q is the expected discounted sum of marginal products of capital. If

the SEO the growth option is exercised and converted into assets in place. Because the assets in place are safer than the growth options, the firm equity is now safer. The equilibrium equity return must drop. This can help account for the long run relatively low returns subsequent to the SEO.

q is directly observable, then there is no need to go further. However it is well-known that the usual measures of q are not satisfactory. This motivated Andrew and Blanchard (1986) to use a vector autoregression to decompose the more basic driving forces that underlie q.

To see how this is done it is helpful to reexpress q. A one-period discount factor is $\beta_{t+s} = (1-\delta)/(1+r_{t+s})$. A one period marginal product of capital is $M_{t+j} = [\pi_K(a_{t+j}, K_{t+j}) - c_K(I_{t+j}, K_{t+j})]/(1-\delta)$. So q_t is rewritten as,

$$q_t = E\left\{\sum_{j=1}^{\infty}\left[\Pi_{s=1}^{j}\beta_{t+s}\right] M_{t+j}|\Omega_t\right\}.$$

Take a first order Taylor expansion for the term inside the expectation around the mean of β_t and M_t. As in Andrew and Blanchard (1986) (equation 7) this gives,

$$q_t = E\left\{\frac{\overline{M\beta}}{(1-\overline{\beta})} + \sum_{j=1}^{\infty}\overline{\beta}^j(M_{t+j}-\overline{M}) + \frac{\overline{M}}{(1-\overline{\beta})\overline{\beta}}\sum_{j=1}^{\infty}\overline{\beta}^j(\beta_{t+j}-\overline{\beta})|\Omega_t\right\}. \quad (2.3)$$

Equation 2.3 decomposes q into: 1) a constant term, 2) a discounted sum of the deviations of the marginal product of capital from the average value, and 3) a discounted sum of the discount factors from the average values.

In order to make use of this setup empirically we need to evaluate both sides of equation 2.3. This requires specifying for the dynamics of β and M. Andrew and Blanchard (1986) use vector autoregressions. We simplify to use an AR(1) model. Later we extend the model to allow for a large number of macro factors using factor-augmented vector autoregressions, in order to see if an extensive range of macrofactors changes our inferences.

The AR(1) assumption says,

$$\begin{aligned}\beta_{t+1} &= \overline{\beta} + \rho_\beta(\beta_t - \overline{\beta}) + \sigma_\beta \varepsilon_{\beta,t+1} \\ M_{t+1} &= \overline{M} + \rho_M(M_t - \overline{M}) + \sigma_M \varepsilon_{M,t+1}\end{aligned}$$

where $\varepsilon_{M,t} \sim N(0,1)$, $\varepsilon_{\beta,t} \sim N(0,1)$, and $\rho_\beta, \rho_M, \sigma_\beta, \sigma_M$ are constants that are known to the firm. This assumption is used to evaluate the three terms on the right hand side of equation 2.3. The first of these is just an expectation of a constant. The second term is given by

$$E\left[\sum_{j=1}^{\infty} \overline{\beta}^j (M_{t+j} - \overline{M}) | \Omega_t\right] = \sum_{j=1}^{\infty} \overline{\beta}^j \rho_M^j (M_t - \overline{M}) = \frac{\overline{\beta}\rho_M(M_t - \overline{M})}{(1-\overline{\beta}\rho_M)}.$$

The third term is given by

$$E\left[\overline{M}(1-\overline{\beta})^{-1}\overline{\beta}^{-1} \sum_{j=1}^{\infty} \overline{\beta}^j (\beta_{t+j} - \overline{\beta}) | \Omega_t\right] = \frac{\overline{M}\sum_{j=1}^{\infty} \overline{\beta}^j \rho_\beta^j (\beta_t - \overline{\beta})}{(1-\overline{\beta})\overline{\beta}} = \frac{\overline{M}\rho_\beta(\beta_t - \overline{\beta})}{(1-\overline{\beta})(1-\overline{\beta}\rho_\beta)}.$$

Substituting these terms back into 2.3 gives,

$$q_t = \frac{\overline{M}\overline{\beta}}{(1-\overline{\beta})} + \frac{\overline{\beta}\rho_M(M_t - \overline{M})}{(1-\overline{\beta}\rho_M)} + \frac{\overline{M}\rho_\beta(\beta_t - \overline{\beta})}{(1-\overline{\beta})(1-\overline{\beta}\rho_\beta)}.$$

We need proxies for both M and β. Since $\beta_t = (1-\delta)/(1+r_t)$, we have $\beta_t \approx 1 - r_t - \delta$. Following Andrew and Blanchard (1986), assume that observable average profit equals unobservable marginal profit. So, $[\pi(a_t, K_t) - c(I_t, K_t)]/K_t = \pi_K(a_t, K_t) - c_K(I_t, K_t)$. It is common to use the ratio of cash flow to capital stock $Cash_t/K_t$ as a proxy for average profit. After simple algebra, the investment regression becomes,

$$\frac{I_t}{K_t} = \alpha_0 + \alpha_1 \frac{Cash_t}{K_t} + \alpha_2 WACC_t. \tag{2.4}$$

According to the model, the coefficients are given by $\alpha_0 = -\frac{1}{\phi} + \frac{\overline{M\beta}}{\phi(1-\overline{\beta})} - \alpha_1 \overline{M} - \alpha_2 \overline{WACC}$, $\overline{WACC} = 1 - \delta - \overline{\beta}$, $\alpha_1 = \frac{\overline{\beta}\rho_M}{\phi(1-\delta)(1-\overline{\beta}\rho_M)} > 0$ and $\alpha_2 = -\frac{\overline{M}\rho_\beta}{\phi(1-\overline{\beta})(1-\overline{\beta}\rho_\beta)} < 0$.[5] The AR(1) assumption thus generates a simple investment regression specification with stark parameter implications. Due to this appealing simplicity we work with equation (2.4) initially. Subsequently we study whether the inferences about the WACC are affected by the introduction of more general macro determinants.

The intercept α_0 is fairly complex. It captures the adjustment cost technology (ϕ), the long run marginal q (i.e. $(\overline{M\beta})/(\phi(1-\overline{\beta}))$), and the product of per unit impact of all future changes in cash flow (α_1) or WACC (α_2) and the number of units in long run ($\overline{M}$ and $\overline{WACC}$).

The impact of cash flow is given by α_1. It captures the proportionality effect, and $(\overline{\beta}\rho_M)/(1-\overline{\beta}\rho_M)$ is a combination of both time discount parameter $\overline{\beta}$ and marginal profit shock persistence parameter ρ_M. In effect it shows the impact of

[5]The model in Liu et al. (2009) (discussed in Lin and Zhang (2013))) makes a similar prediction on α_2. Following the notation of the two-period model in Lin and Zhang (2013), r^{Ba}_{it+1} is the the after-tax corporate bond return for firm i on date $t+1$, r^S_{it+1} is the return on equity, w_{it} is the market leverage, $a > 0$ is the adjustment cost parameter, I_{it} is investment, K_{it} is the firm's capital stock, Π_{it+1} is the marginal benefit of extra unit of capital over period t+1. Lin and Zhang (2013) shows that

$$1 + a(\frac{I_{it}}{K_{it}}) = \frac{\Pi_{it+1}}{w_{it} r^{Ba}_{it+1} + (1-w_{it}) r^S_{it+1}}.$$

This equation says that the marginal cost of installing extra unit captial over preriod t should be equal to the present value of the marginal benefit brought by this extra unit capital over period t+1. The discount factor is $w_{it} r^{Ba}_{it+1} + (1-w_{it}) r^S_{it+1}$ which is WACC. We know that $a > 0$, $1 > w_{it} > 0$, and $\Pi_{it+1} > 0$. Accordingly we see that a high cost of equity (debt) is associated with a low investment to capital ratio. Thus the impact of the cost of equity (debt) has the same sign as in Andrew and Blanchard (1986).

all future marginal profit shocks on the optimal investment.

To get the impact of WACC, we take a first order approximation. As a result changes in β_t are an affine function of the changes in WACC with the opposite sign. This implies that we should observe a negative sign on α_2. In α_2, the term $(\rho_\beta)/(\phi(1-\overline{\beta})(1-\overline{\beta}\rho_\beta))$ captures the proportional factor. The product of this proportional factor and $\overline{M}$ transforms these future expected changes in WACC in terms of marginal profit which determines today's optimal investment. We assume the long run mean of WACC and cash flow are constant, so the variation in WACC and cash flow is equivalent to their deviation from their long run mean.

2.3 Data and Descriptive Statistics

The firm level data is from Compustat and CRSP and the macro data is from the St. Louis Federal Reserve's collection (http://research.stlouisfed.org/fred2/). Firm level data is winsorized at 1% in each tail. Industry definitions follow Fama and French (1997). We omit firms in utilities, banking, insurance, real estate, trading, and with a missing industry code.[6]

Table I provides a number of descriptive statistics. The sample starts in 1955, ends in 2011, and includes 10,624 firms. The average firm appears in the data for 24.5 years. Due to data limitations the total number of firm-years that are useable is about 75,000. The mean firm has an investment-to-capital ratio of 0.180, but the median is just 0.118. The distribution is not symmetric. Figure 1 shows the

[6]There are a remarkably large number of possible proxies that can be used for each component of the WACC. In an earlier draft of this paper we reported results for 440 different versions. The basic empirical results are quite robust. The main dividing line is the two classes of approaches to the cost of equity capital that we report in this paper. Other things, such as using industry averages to get betas in place of firms specific regressions, are not terribly important for the inferences to be drawn.

mean investment-to-capital ratio. This constructed for each year by considering the distribution for the firms that are active in that year. In the early 1980s and the mid 1990s this ratio was well above 0.2, while in the early 1960s and 2009 this ratio was below 0.1. So there is a fair bit of time-series variation.

The mean cost of equity is about 20%. For the cost of equity, depending on the proxy, the 5th percentile is about 1/10th the cost of the 95th percentile. The plot of the Carhart version of the cost of equity shows that it was fairly flat from 1955 to about 1980. Then it spiked up during the Volker period, after which it gradually declined to about 0.15. The Gordon growth model version of the implied cost of equity capital has a rather different pattern. From 1955 to 1975 it increased. After the early 1980s it was falling until the financial crisis. Starting in about 2007 it shot back up. So these alternative approaches to the cost of equity have similar mean values, but they exhibit very different time-series variation.

To measure the cost of debt r_D it is common to use the actual yield on the debt the firm is currently carrying. This method is particularly simple to compute and to interpret and we use it as the main case. However, the method is frequently criticized since it does not necessarily reflect the current debt market conditions facing the firm. The cost of debt computed this way will generally appear to be much smoother than the actual debt market rates. As an alternative we computed the average yield of the firm's incremental debt issued during the year. This method should more closely reflect current market conditions in the given year. However, the inferences to be drawn were not affected. So we stick with the simpler calculation in the reported results.

Figure 2 shows the cost of debt. The mean corporate cost of debt is about half the cost of equity at 10.8%. The cost of debt also has a huge spread so that the 5th percentile value is about 1/8th the 95th percentile. Similar to the cost of government debt, the cost of corporate debt increases fairly steadily from 1955 to about 1980. But after 1980 there is fairly regular fluctuation, but only a very modest degree of decline.

For leverage we use the target leverage as generated by the Frank and Goyal (2009). Several alternatives were also tried (realized book leverage, realized market leverage, an equally weighted sum of market leverage and industry median), and they result in the same inferences. The mean target leverage is about 0.28 which is very close to the long term average for the USA economy as reported in the Flow of Funds data since the Second World War. The lower panel of Figure 2 shows a spike in leverage in the mid 1970s followed by a declining trend.

The average income tax rate paid by a firm is a frequently used proxy for the firm's marginal tax. The average tax rate according to this proxy is about 35.7%. This proxy will be a good measure if the firm's tax rate is very persistent from year to year. It also has the merit of simplicity and easy availability. We thus use it as our primary proxy. However it also has drawbacks. The most important may be the lack of real exogeneity. Figure 3 shows that there is a long term decline in the corporate tax between 1955 and 1990. After 1990 corporate tax is fairly flat.

The top statutory federal corporate income tax rate has the advantage that it is actually exogenous to a given firm. However the tax code is complex, and not all firms are paying the top marginal rate. We tried using this measure and it does not change our inferences.

More sophisticated tax measures are available for recent years from the study by Graham and Mills (2008). They include more of the tax code structure. We examined the impact of two measures considered in that study. The first is the simulated tax which covers the period from 1980 to 2010. The problem is that it does not cover all the firms. The second measure is the OLS predicted tax, which covers a large portion of our sample. The alternative tax code measures do make some difference, primarily for the CAPM and Fama-French cost of equity approaches. The tax effects are small enough empirically that the main results on the cost of debt and equity do not hinge on the choice of tax proxy.

Table II provides several correlations. As expected investment is positively correlated with q and with cash. It is negatively correlated with the cost of debt and with leverage. The correlation between investment and the cost of equity depends on how the cost of equity is measured. The cost of equity can be computed in many ways. The key dividing line is between historical methods (CAPM, Fama-French etc.) and implied cost of equity capital methods such as the Gordon growth model.

2.4 Investment Regression Results

Table III provides investment ratios for firms sorted by cash flow and WACC. Firms are sorted annually into quintiles as a function of the Cash/K ratio and a WACC measure. This allocates each firm-year observation into one of 25 cells. Within each cell the average investment to capital ratio is computed. The same procedure is carried out for a version of the WACC in which the cost of equity is computed with CAPM, and also a version that uses the Carhart model.

Consider the CAPM version starting with the Total column. As the CAPM increases the investment ratio also increases from 0.131 in the bottom quintile to 0.183 in the top quintile. The difference between the top and the bottom is statistically significant ($p < 0.01$). When firms are also sorted accoring to cash flow a very similar pattern is found in each of the five columns. As expected high cash flow firms invest more than low cash flow firms. But within each Cash quintile, as WACC increases so too does investment.

The bottom part of Table III give the Carhart version of WACC. Strikingly similar results are observed. Investment is increasing in Cash and in WACC. The same patterns were obtained using the Fama-French model as well although these are not reported to save space.

Table III is a problem for the Abel-Blanchard model. In the model, high WACC means future cash flows are worth less than they are for low WACC. Accordingly high WACC firms should invest less – contrary to what is observed. It is therefore important to get the the heart of this surprising investment pattern.

A natural concern is that some type of omitted firm effect or year effect is being picked up inadvertently. Accordingly Table IV reports investment regressions that include firm and year fixed effect. Similar results are obtained if either type of fixed effects are included without the other one. Columns 1, 2 and 3 use contemporaneous versions of the WACC. Using the CAPM the WACC is not statistically significant. Using the Fama-French model a negative and significant sign is found on the WACC. Using the Carhart model a positive and significant sign is obtained.

The instability across columns 1 - 3 was surprising. So in columns 4 - 6 we redo the regressions that we use lagged versions of the explanatory variables. Now much more consistent results are obtained. In all three versions investment is again increasing in the WACC. Thus columns 4 - 6 provide robust results that parallel the results in Table III. But this does not really explain the instability observed in columns 1 - 3. This instability motivates a decomposition of the WACC.

Table V repeats the regressions from columns 1 - 3 in Table IV, but without the composite WACC. Instead the equity group of terms ($\frac{E}{V}r_E$) is included as a factor separately from the debt group of terms ($\frac{D}{V}r_D(1-\tau)$). In columns 1 - 3 the sign on the debt term is consistently and strongly negative. The sign on the equity term is now consistently positive. Recall that the WACC is a weighted sum of these two parts, and that empirically the cost of equity gets a higher weighting. This helps explain why a degree of instability might have been found in Table IV. Columns 1 - 3 thus reinforce the empirical results from Table III that are contrary to theory.

In the empirical literature on investment it is common to include q along with other factors in an investment regression. Under the Abel-Blanchard model q does not belong in the regression. However, we have been asked whether omitting q in columns 1 - 3 is generating misleading results.[7] Accordingly columns 4 - 6 report regressions in which q is added as an explanatory variable. As expected q has a positive sign and is statistically significant. It leaves that negative sign on the debt group of terms intact. Q does take away from the power from the equity group of terms. Under the CAPM and Carhart models the cost of equity continues to be positive and statistically significant. Under the Fama-French model (column 5) the coefficient is still positive, but is now not statistically significant. Thus q and the cost of equity terms are reflecting related information.

Table VI takes the decomposition one step further. Now leverage, cost of debt, cost of equity and tax terms are all entered separately and linearly. Otherwise the 6 columns match the 6 columns from Table V. The Fama-French version of the cost of equity (Columns 2 and 5) is not significantly different form zero. The other two versions of the cost of equity remain significantly positive. The cost of debt is always negative and significant.

An interesting result concerns leverage. When q is not included, leverage has a negative and significant coefficient. However when q is added to the model, the

[7] For instance one might argue to include q as a sufficient statistic. Then the inclusion of the WACC terms can be viewed as a check of the status of the empirical proxy for q.

effect of leverage becomes zero. In effect, q appears to fully subsume the effect of leverage on investment.

Tables V and VI provide a fairly clear result. The cost of debt has a negative effect on investment. The CAPM and Carhart versions of the cost of equity have a positive effect on investment. Since this result is contrary to the Abel-Blanchard theory we next study the extent to which this result is true across time and across the decades.

In corporate finance it is often found that small and large firms have significant differences. To what extend does this distincation affect our results? Table VII reports results that are similar to columns 1 - 3 in Table VI, however we report separate results for the largest and smallest quintile of firms.

In Table VII, the empirical results are much stronger for large firms. Among the large firms, all of the effects match columns 1 - 3 in Table VI. Among the small firms the tax effects and the cost of equity effects become statistically insignificant. The explanatory power of the regressions also drop almost by half when compared to the large firms. Notably the impact of cash seems to be a bit stronger among the smallest firms than it is among the largest firms. While these results help refine our understanding of the data, they do not resolve the cost of equity issue.

Chen and Chen (2012) document that cash flow has become less important (relative to q) in recent decades. Could the declining importance of cash harm our inferences about the role of WACC? To answer this question, Table VIII provides results by decade. According to our model q does not belong in the specification. So some differences from Chen and Chen (2012) are to be expected.

Consistent with Chen and Chen (2012), over the decades the important of cash does weaken measurably. However in our tests it retains significance. The effect of leverage is statistically insignificant during the 1970s. But in more recent decades, more highly levered firms invest less. The cost of debt effect shrinks in magnitude over time. However, in each decade higher cost of debt means less corporate investment.

The tax effect is significant in every decade. In the 1970s and 1980s it is negative and significant. In the 1990s and the 2000s it is positive and significant. Such instability suggests that the tax variable is problematic. Presumably the tax measure is not properly reflecting what it is assumed to be measuring in the WACC. Similar instability is found when other tax proxies are used.[8]

Our real concern is over the cost of equity terms. A disconcerting degree of instability is observed. The CAPM cost of equity is positive and significant in the 1980s and 1990s, but insignificant in the 1970s and the 2000s. The Fama French cost of equity is insignificant in the 1980s and 1990s. The Carhart cost of equity is positive and significant in the 1970s, 1980s and 1990s, but not significant in the 2000s.

We do not observe any clear cut time trend in the results for the cost of equity across the decades. The coefficient instability is a worrying sign. It seems as if these three measures of the cost of equity are not doing the job that is assumed in the theory. Something deeper might be needed.

2.5 Endogenous Stochastic Discount Factor

Perhaps the reason that we get a problematic result for the cost of equity is that the Andrew and Blanchard (1986) theory does not explicitly model the co-movement of cash flow, investment, and cost of equity. These observable firm

[8]The puzzling impact (or lack of impact) of tax variables is an ongoing issue in corporate finance more broadly. Solving the tax issue is far beyond the scope of the current paper. It will likely require access to much more detailed data on corporate tax payments than is publicly available.

metrics may be driven by the same latent economics forces, and this may change model prediction.

An appealing and influential model that addresses this issue is provided by Zhang (2005). In the model, firm's cash flows and investment are affected by both idiosyncratic and aggregate shocks, while the stochastic discount factor is driven by aggregate shocks. Following Berk et al. (1999), it is assumed that the stochastic discount factor β_t from time t to t+1 is parameterized as a function of the aggregate shocks x_t, $log\beta_t = log\beta + \gamma_t(x_t - x_{t+1})$ and $\gamma_t = \gamma_0 + \gamma_1(x_t - \overline{x})$ where $\beta > 0$ is the discount factor in static case, $\gamma_0 > 0$ is constant price of risk, and $\gamma_1 < 0$ is the time-varying price of risk. Otherwise the model is very similar to Andrew and Blanchard (1986).[9]

We solve the model numerically using the code provided by Lin and Zhang (2013). After solving the model, we simulate a panel of 1000 firms and 800 periods. We drop the firms with negative stock price or negative average cash flow. For each firm we keep the last 606 periods. In the end we have 920 firms and 606 periods.

To match the model terms with data we follow Zhang (2005). Let the cum-dividend firm value in the model be $V_{i,t}$, while the one period cash flow is $Cash_{i,t} = d_{i,t} = \pi_{i,t} - f - I_{i,t} - h(I_{i,t}, K_{i,t})$ where f is the fixed cost and $h(I_{i,t}, K_{i,t})$ is the adjustment cost function. The time period t expected stock return is $r_{E,i,t} = E_t(r_{i,t+1}) = E_t(V_{i,t+1})/(V_{i,t} - d_{i,t})$ where $(V_{i,t} - d_{i,t})$ is the ex-dividend firm value.

Using the simulated data we estimate the following equation,

$$\frac{I_{i,t}}{K_{i,t}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t}} + \alpha_2 r_{E,i,t} + \varepsilon_{i,t}.$$

[9]The model also makes use of a more flexible adjustment cost specification and a slightly different production function.

The key question is the sign of α_2. Let $\widehat{x}$ denote the estimated value of any parameter x.

Recall that according to the model of Andrew and Blanchard (1986) with real data we should should have found $\widehat{\alpha}_2 < 0$. But we did not.

Does the Zhang (2005) model reverse the *prediction*? We ask this both in the time dimension and in the cross section. Figure 2 plots histograms of estimated coefficients and the associated t-statistics from pure time-series regressions on data from the simulated firms. It is quite clear that the typical coefficient is negative and statistically significant at conventional levels. The typical coefficient value is about -0.45 with a t-statistic of about -5. Equivalent results were obtained in the cross-section. The negative sign is obtained both for contemporaneous cost of equity and for lagged. The negative sign on the cost of equity is a pretty robust implication of the model. To save space these results are not tabulated.

Changing to a popular model that allows for an endogenous stochastic discount factor does not resolve the conundrum. This model too has a problem with the impact of the cost of equity on corporate investment.

2.6 Allowing for Macro Factors

The results presented so far show that the impact of the cost of equity is a problem. Perhaps the basic empirical framework is misspecified. The estimating structure used so far assumes that the discount factor and the cash flows have a simple AR(1) structure. Perhaps this simplification is the source of the trouble.

To address this concern we next replace the AR(1) assumption by including a large number of macroeconomic series and allow them to influence the dynamics. To do this we adopt a factor augmented vector autoregression approach.

To see how this works, start with the setting. Suppose the data is a $T \times N$ panel with elements x_{it}, where $i = 1, ...N$ and $t = 1, ...T$. Assume that x_{it} has a factor structure $x_{it} = \lambda_i F_t^{\varphi} + e_{it}$, where $\varphi \in \{\beta,\, M\}$. F_t^{φ} is a low dimensional $(n^{\varphi} \times 1)$ vector of latent common factors with $n^{\varphi} \ll N$.

As described by Ludvigson and Ng (2009), F_t^{φ} is estimated by principal components. Let $Z_t^{\varphi} = \begin{bmatrix} \varphi_t \\ f_t^{\varphi} \end{bmatrix}$, where $\varphi_t \in \{\beta_t, M_t\}$ and f_t^{φ} is a $(K^{\varphi} \times 1)$ vector with $f_t^{\varphi} \subset F_t^{\varphi}$. Let $\varphi_t = b' Z_t^{\varphi}$ where b is a $(K^{\varphi} + 1) \times 1$ vector with the first element equal to one and the other elements equal to zero.

It is assumed that,

$$Z_{t+1}^{\varphi} = \overline{Z}^{\varphi} + A^{\varphi}(Z_t^{\varphi} - \overline{Z}^{\varphi}) + \sigma_Z^{\varphi} \varepsilon_{t+1}^{\varphi},$$

where A^{φ} and σ_Z^{φ} are $(K^{\varphi}+1)\times(K^{\varphi}+1)$ matrices, while Z_t^{φ} and ε_t^{φ} are $(K^{\varphi}+1)\times 1$ vectors. If the first element in A^{φ}, $\rho_{\varphi} > 0$, and all other elements are set to zero, then the model reduces to the AR (1) process considered above.

We estimate the common factors f_t^{φ} by three steps:

1. A balanced panel of major macroeconomic time series data and firm time series data (median across all firms each year) from 1955 to 2011 was collected. A list of the variables is in Table 2.11.

2. Principal component analysis was used to extract a small number of common factors F_t^{φ} from this large number of time series. For β_t we keep the first 10 components ($K^{\beta} = 10$), and for M_t we keep the first 12 components ($K^M = 12$).

3. Next we run OLS regressions using $\{\beta_t, M_t\}$ as the dependent variables. The independent variables include factors (F_t^{φ}), all two-factor interactions, and

> squared factor items. All independent variables are lagged by one period. The Bayesian information criterion (BIC) is used to select factors. We search over all possible combinations of independent variables and find the one that gives the minimum BIC. This gives us a $K^{\varphi} \times 1$ vector of factors $f_t^{\varphi}$with $K^{\varphi} \leq n^{\varphi}$.

As a result of this procedure, 3 factors are selected for WACC, and 4 factors for cash flow. The interpretation of the factors is always a concern with principal components. To address this we run univariate regressions of each macro variable on each extracted factor. In the appendix we plot the R^2 from these univariate regressions.

For four of the factors the interpretation of the extracted factor seems clear. The WACC factors reflect interest rates, stock market returns, and exchange rates. The first cash flow variable is related to a number of 'state of the business cycle variables' such and unemployment and payrolls. The three remaining cash flow factors have less easy interpretations. Fortunately our results do not hinge on whether they are included or left out.

After we get f_t^{φ}, we run a vector autoregression for WACC and cash flow. The coefficient matrix A^{φ} is recorded and used to construct the variables in the regression. The regression is

$$\frac{I_t}{K_t} = \alpha_{\beta M} + \alpha_{\beta} x_{\beta,t} + \alpha_M x_{M,t} \tag{2.5}$$

with $\alpha_{\beta M} = -\frac{1}{\phi} + \frac{\overline{M\beta}}{\phi(1-\overline{\beta})}$, $\alpha_{\beta} = \frac{\overline{M}}{\phi(1-\overline{\beta})} > 0$, $x_{\beta,t} = b'(I - A^{\beta}\overline{\beta})^{-1}A^{\beta}(Z_t^{\beta} - \overline{Z}^{\beta})$, $\alpha_M = \frac{\overline{\beta}}{\phi} > 0$, and $x_{M,t} = b'(I - A^{M}\overline{\beta})^{-1}A^{M}(Z_t^{M} - \overline{Z}^{M})$.

The empirical implementation in Andrew and Blanchard (1986) can be viewed as a special case of this dynamic factor model. Instead of extracting factors from the whole panel of data, they use a very restricted set of plausible data for the analysis.

Table IX reports the results of estimating equation 2.5. Theory predicts $\alpha_\beta > 0$ and $\alpha_M > 0$. Empirically $\alpha_\beta < 0$. This coefficient estimate is in line with the earlier results on the cost of equity terms.

The introduction of macro factors provides interesting connections between the WACC and macro conditions. But it does not resolve the problematic cost of equity impact on corporate investment.

2.7 Implied Cost of Equity Capital

Our final approach to resolving the equity problem follows papers such as Chava and Purnanandam (2010) and Gebhardt et al. (2001). The idea is that observed historical returns on equity provide a poor proxy for expected returns on equity. It has been argued that the CAPM and related models do a poor job of reflecting the expected cost of equity.

There are several versions of the implied cost of equity capital. The most traditional is the Gordon Growth Model (GGM) while recently a Residual Income Model (GLS) is popular. Some scholars like to use analyst forecasts (IBES), while others (Hou et al., 2011) prefer to use a statistical model to predict earnings. We use both approaches and obtain similar results. There is also a decision of how far in the future to do explicit projections. We have tried numbers ranging from 1 to 5 years and report results for 5 years. Despite all this variety, the results are are quite similar across versions.

In both GGM and GLS models some type of cash flow projections are made. Then the question is what discount rate is needed to enable those projected cash flows to be valued at the current stock market value of the firm's equity. The stock market value is directly observed. But the expected cash flows must be obtained.

The more common approach is to use earnings forecasts from stock analysts. These forecasts are available from the IBES database. The earnings forecast in IBES generally range from one to five years. A long term growth rate is also provided for some firms. We use the median of earnings forecast and we report results from the 5 year horizon. We have run all results using the 1 year data as well, and the results are the same.

There are drawbacks to using analyst forecasts. Analysts only cover a subset of firms, and their forecasts might not reflect more general opinions of the marginal investor. It is hard to know. This motivated attempt to make statistical forecasts that can be applied more broadly.

Hou et al. (2011) (HDZ) and Lee et al. (2010) report that a simple statistical model can be used to predict earnings. To see how their approach works start with the following notation: $EV_{j,t}$ denote the enterprise value of firm j in year t, TA is total assets, DIV is the value of dividends paid, DD is a dummy for paying dividends, $E_{j,t}$ is earnings (before extraordinary items) by firm j in year t, $NegE$ is a dummy for negative earnings, ACC is total accruals divided by total assets.

They estimate $E_{j,t+\Delta t} = \alpha_0 + \alpha_1 EV_{j,t} + \alpha_2 TA_{j,t} + \alpha_3 DIV_{j,t} + \alpha_4 DD_{j,t} + \alpha_5 E_{j,t} + \alpha_6 NegE_{j,t} + \alpha_7 ACC_{j,t} + \varepsilon_{j,t+\Delta t}$. This model is estimated using pooled cross-section regressions with a rolling ten year prior window of data for each year. For comparability we do the same. The time gap Δt ranges from 1 to 5.[10]

Following Lee et al. (2010), $r_{E,GGM,IBES5}$ is the estimated cost of equity using

[10]In Hou et al. (2011): E is net income or earnings before extraordinary items (ib); EV is total asset (at)+market value of equity-book value of equity; DIV is dividend payment (dvt); TA is total asset (at); ACC is change in current assets (act)+ change in debt in current liability(dlc) - change in cash and short term investment(che) -change in current liabilities(lct), then scaled by total asset (at).

the Gordon Growth Model and analyst earning forecasts from IBES. To obtain this value we solve the following equation:

$$P_t = \sum_{i=1}^{4} \frac{DPS_{t+i}}{(1 + r_{E,GGM,IBES5})^i} + \frac{EPS_{t+5}}{r_e(1 + r_{E,GGM,IBES5})^4}$$

with,

$$DPS_{t+1} = EPS_{t+1} \times \kappa$$

where dividend payout ratio κ follows Hou et al. (2011) and Gebhardt et al. (2001) (GLS). If earnings are positive, κ is the current dividends divided by current earnings. If earnings are negative, κ is the current dividends divided by $0.06\times$total assets.

Gebhardt et al. (2001) (GLS) suggest a Residual Income approach. Thus $r_{E,GLS,IBES}$ is a Residual Income Model (GLS) using IBES-based earnings per share forecast. We follow Gebhardt et al. (2001) and Hou et al. (2011) to solve the following equation,

$$M_t = B_t + \sum_{i=1}^{11} \frac{E_t[(ROE_{t+i} - r_e) \times B_{t+i-1}]}{(1 + r_{E,GLS,IBES})^i} + \frac{E_t[(ROE_{t+12} - r_e) \times B_{t+11}]}{r_{E,GLS,IBES}(1 + r_{E,GLS,IBES})^{11}}$$

where M_t is the market value of equity, B_t is the book value of equity. Book value of equity[11] follows Davis et al. (2000). The book value of equity evolves according to

$$B_{t+i} = B_{t+i-1} + Earning_{t+i}(1 - \kappa)$$

[11]Particularly, book value of equity=stockholder equity (seq) +balance sheet deferred taxes(txdb)+balance investment tax credit (itcb)-book value of preferred stock; book value of preferred stock=in order: redemption(pstkrv), liquidation(pstkl), or par value(pstk) of preferred stock; if stockholder equity (seq) is not available, then stockholder equity=book value of common equity(ceq)+par value of preferred stock(pstk), or stockholder equity=book value of total assets(at)- book value of total liability (lt).

where B_t and κ are defined the same as before, and $Earning_t$ is from IBES.

Return on equity ROE_{t+i} is defined as follows. From year one to year three it is the $\frac{Earning_{t+i}}{B_{t+i-1}}$. From years four to year twelve, it is the interpolated value between ROE_{t+3} and industrial median at time t. Industrial median excludes firms with negative earnings.

Finally, Hou et al. (2011) provide another closely related method. For details, see their paper.

The results from five different implied cost of equity capital methods are reported in Table X. Due to data requirements, these results are for data from 1980 to 2011.

In all cases cash has a positive effect on equity, leverage a negative effect, the cost of debt has a negative effect and tax effects are variable. These results are consistent with the earlier findings and show that changing the cost of equity proxy does not affect the inferences about these other effects.

More important are the coefficients on the cost of equity. Under all five models the coefficient is negative, and in all but one case the coefficients are statistically significant. These results are sharply at odds with the earlier results. The reported results assume 5 years of forecasting, but similar results are obtained with shorter forecasting horizons.

This evidence provides a plausible resolution of the puzzle. Our evidence is consistent with Hou et al. (2011) when they claim that, 'noisy ex post realized return' on equity does not provide a good estimate of 'ex ante expected return' on equity. A similar effect appears to be at work along the dimension that we investigate.

2.8 Conclusion

This paper provides evidence on the impact of the cost of capital on corporate investment. The results are summarized in the introduction, so we do not repeat them here. The evidence presents a tension between rejecting very appealing and well-established theoretical models of corporate investment, or rejecting very appealing and well-established empirical approaches to expected equity returns. Naturally, taste will differ.

The standard models of corporate investment might gain from greater attention to inclusion of stochastic arrival of real investment options. In that way a firm with a high 'cost of equity' would be a firm that has had a large number of arrivals of beneficial investment opportunities. That might provide an alternative explanation for the empirical connection between corporate investment and the more traditional approaches to empirical asset pricing – without going to the implied cost of equity approach.[12]

There are several closely related versions of the implied cost of equity capital. They perform quite reasonably in our tests. On the dimension that we study, these methods behave rather similarly to each other. It might be useful to determine the relative merits of alternative implied cost of equity capital methods on other dimensions.

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[12] This idea might be developed by extending the approach in Carlson et al. (2006) to a more general setting in which there is an ongoing flow of options arriving and being exercised, rather than one big option that triggers the SEO. In doing such an extension some care would need to be taken regarding the timing. How much of the time is like the 'pre SEO' with high stock returns, and how much of the time is like 'post SEO' with low stock returns? A closely related idea is in the Pastor and Veronesi (2005) study of IPOs.

Figure 2.1: Cost of Equity, 1955 to 2011

The figures below show the average of investment (I/K) and cost of equity ($r_{E,Car}$ and $r_{E,GGM,HDZ}$) for all firms from 1955 to 2011. The accounting data are from the COMPUSTAT/CRSP merged file. The stock return data are from CRSP. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. See appendix for data details.

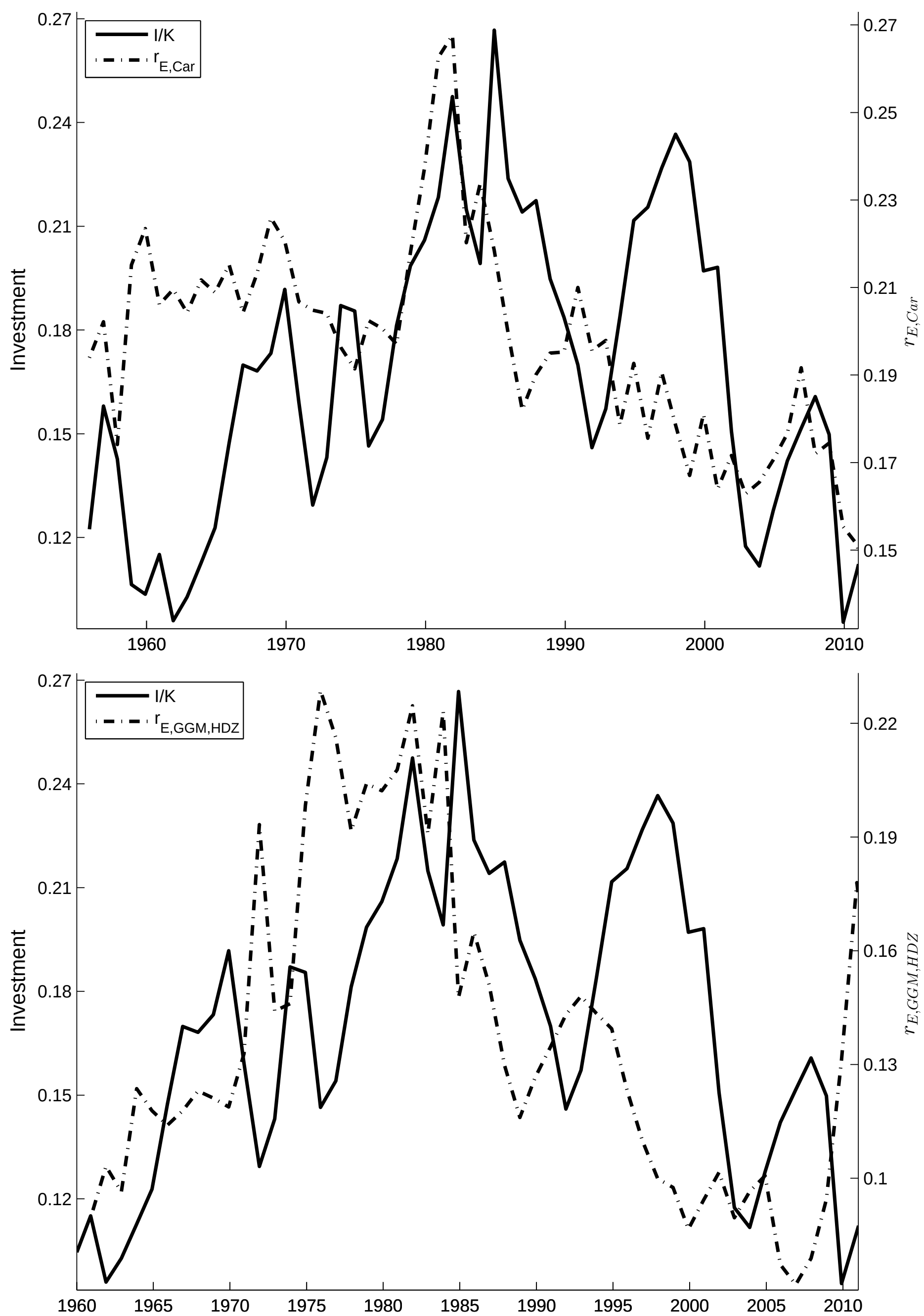

Figure 2.2: Cost of Debt and Leverage, 1955 to 2011

The figures below show the average of investment (I/K), cost of debt (r_D), and leverage(Lev) for all firms from 1955 to 2011. The accounting data are from the COMPUSTAT/CRSP merged file. The stock return data are from CRSP. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. See appendix for data details.

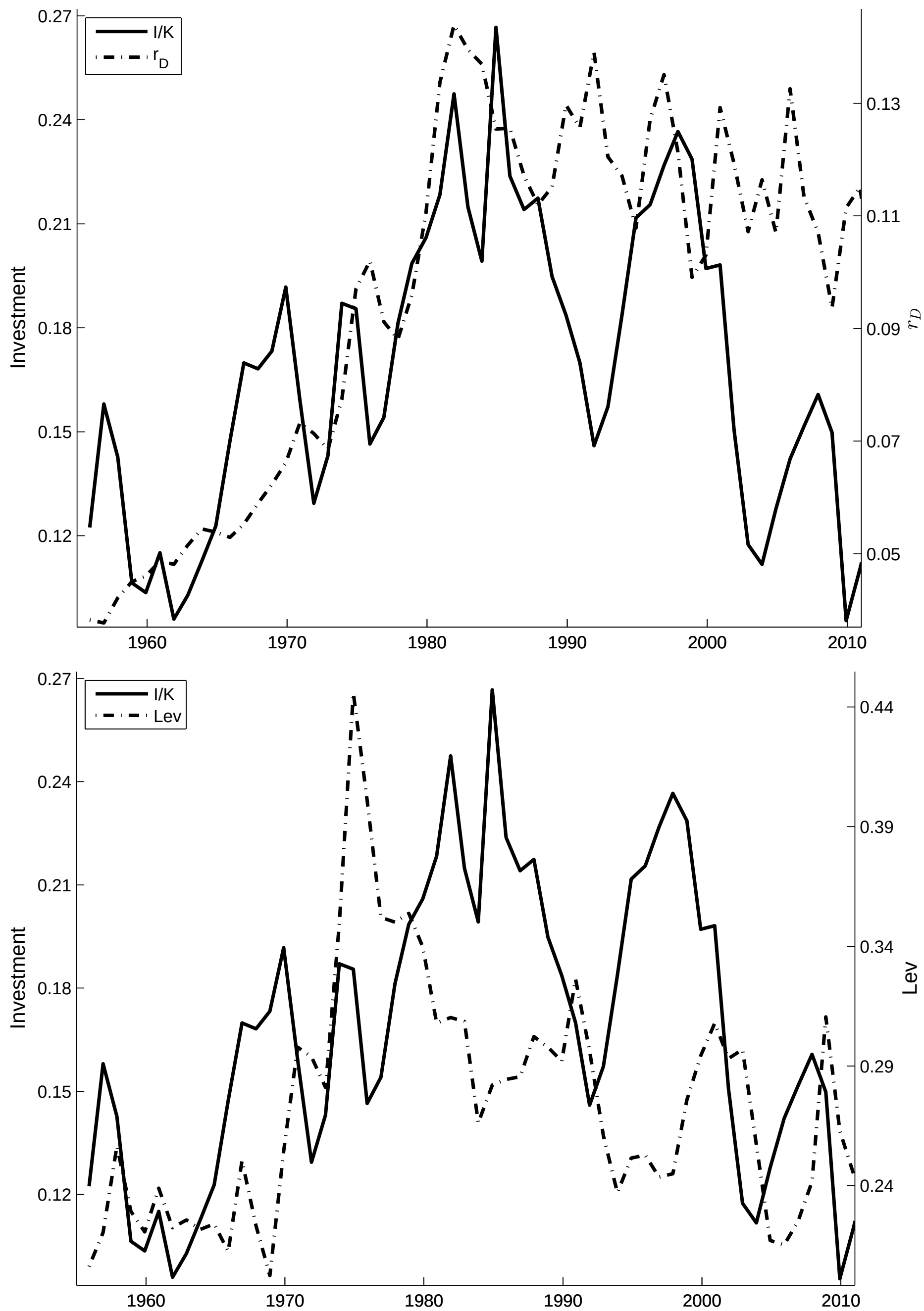

Figure 2.3: Cash Flow and Corporate Tax, 1955 to 2011

The figures below show the average of investment (I/K), cash flow ($Cash/K$), and corporate tax (Tax) for all firms from 1955 to 2011. The accounting data are from the COMPUSTAT/CRSP merged file. The stock return data are from CRSP. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. See appendix for data details.

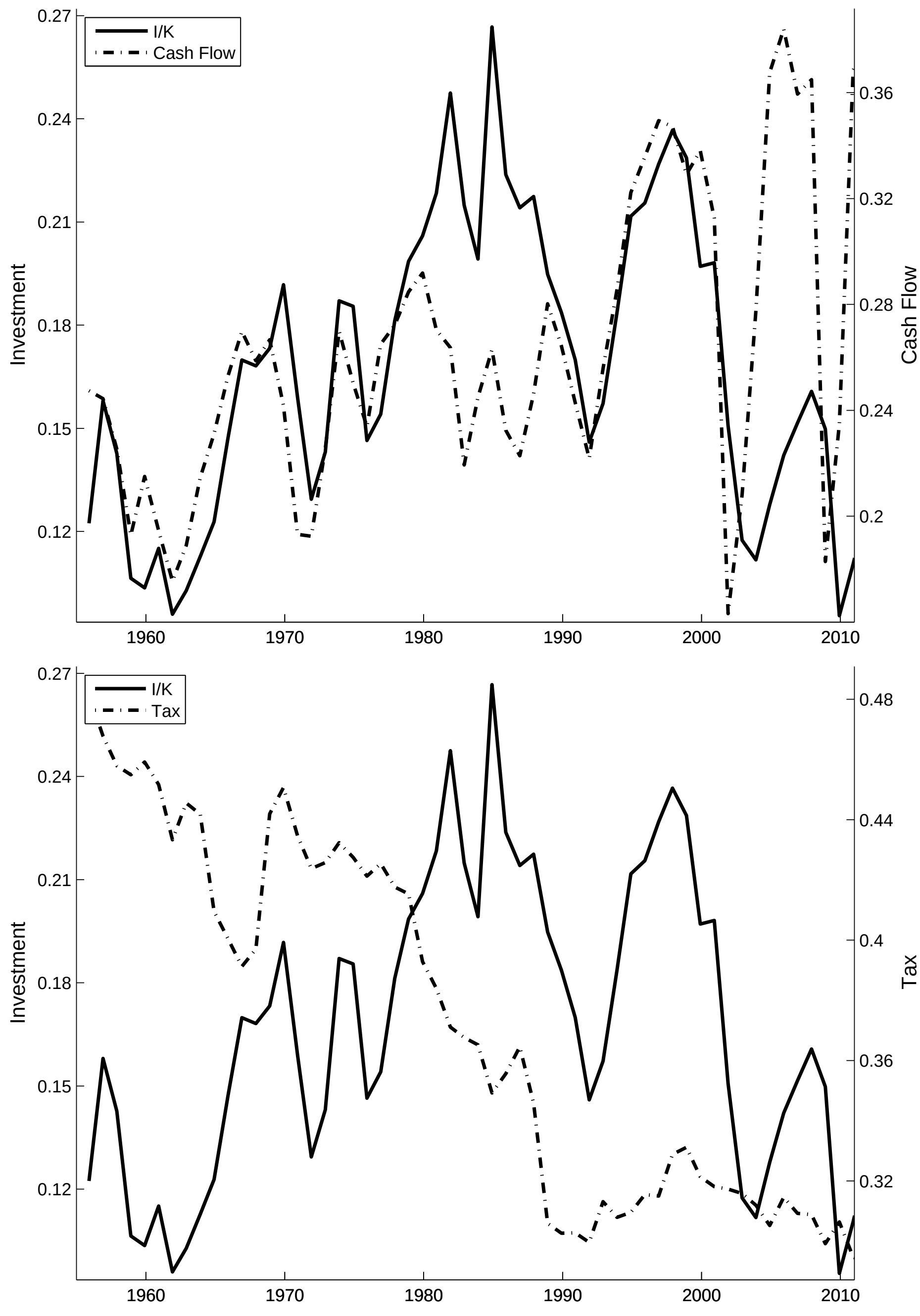

Figure 2.4: Simulated Data from the Model of Lin and Zhang (2013)

The histograms below plot the estimates from the regressions using a simulated panel of data. The model and computing code is from Lin and Zhang (2013) (a slightly different version of Zhang (2005)). After solving the model, we simulate a panel of 1000 firms and 800 periods. We drop the firms with negative stock price or negative average cash flow. For each firm we keep the last 606 periods. In the end we have 920 firms and 606 periods. The expected stock return $r_{E,i,t}$ is defined as $E_t(r_{i,t+1}) = E_t[V(i,t+1)]/[V(i,t) - Div(i,t)]$. The cash flow $Cash_{i,t}/K_{i,t}$ is defined as $Div(i,t)/K(i,t)$. See Zhang (2005) for details of $V(i,t)$, $Div(i,t)$, and the model. The regression equation we estimate is

$$\frac{I_{i,t}}{K_{i,t}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t}} + \alpha_2 r_{E,i,t} + \varepsilon_{i,t}.$$

For each firm, we run a pure time series regression and record the coefficient on the $r_{E,i,t}$ and its t-statistics. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The upper histogram plots the coefficients. The lower histogram plots the t-statistics.

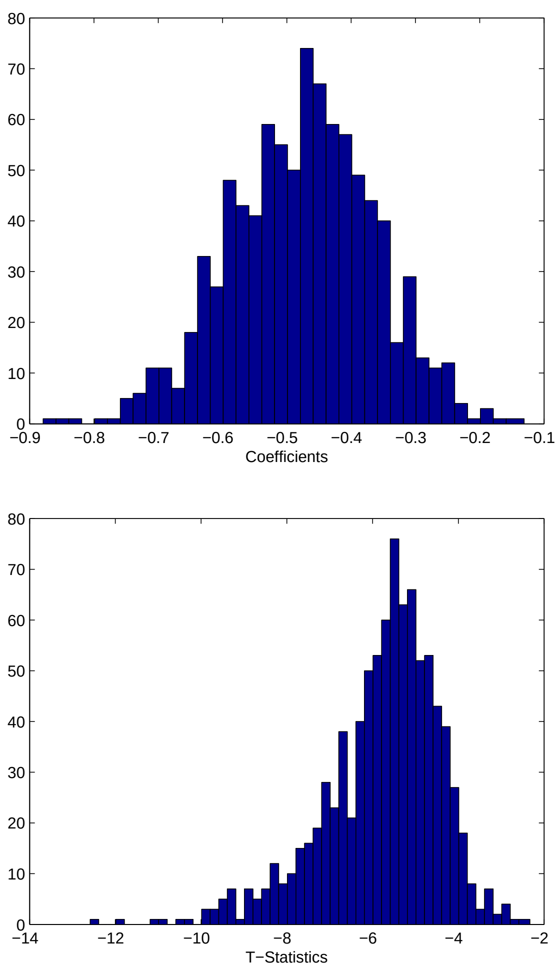

Table 2.1: Descriptive Statistics

This table presents the descriptive statistics of the main variables in the paper. The accounting data come from the COMPUSTAT/CRSP merged file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Q is (Item AT + Item PRCC×Item CSHO - Item SEQ -Item TXDB)/ Item AT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. $r_{E,GGM,HDZ}$ is the cost of equity from Gordon Growth Model with model predicted future earnings as in Hou et al. (2011). Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. $wacc_{CAPM} = r_{E,CAPM} \times (1-Lev) + r_D \times Lev \times (1-Tax)$, $wacc_{FF3} = r_{E,FF3} \times (1-Lev) + r_D \times Lev \times (1-Tax)$, and $wacc_{Car} = r_{E,Car} \times (1-Lev) + r_D \times Lev \times (1-Tax)$.

	n	mean	median	std.	p5	p95
I/K	127647	0.180	0.118	0.207	0.025	0.547
$Cash/K$	130125	0.275	0.188	0.492	-0.121	1.081
$r_{E,CAPM}$	99510	0.202	0.199	0.077	0.080	0.338
$r_{E,FF3}$	99101	0.202	0.198	0.076	0.081	0.336
$r_{E,Car}$	95926	0.195	0.188	0.093	0.052	0.364
$r_{E,GGM,HDZ}$	47491	0.148	0.109	0.120	0.035	0.407
r_D	121443	0.108	0.084	0.134	0.031	0.225
Lev	134265	0.285	0.283	0.115	0.103	0.477
Q	129286	1.626	1.277	1.164	0.716	3.733
Tax	130129	0.357	0.386	0.148	0.000	0.533
$wacc_{CAPM}$	78028	0.161	0.155	0.060	0.073	0.268
$wacc_{FF3}$	77784	0.161	0.155	0.058	0.076	0.263
$wacc_{Car}$	75675	0.157	0.149	0.070	0.055	0.285
number of firms	10624		average years	24.49		

Table 2.2: Correlations

This table presents the correlation matrix of the main variables in the paper. The accounting data come from the COMPUSTAT/CRSP merged file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Q is (Item AT + Item PRCC×Item CSHO - Item SEQ -Item TXDB)/ Item AT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. $r_{E,GGM,HDZ}$ is the cost of equity from Gordon Growth Model with model predicted future earnings as in Hou et al. (2011). Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. $wacc_{CAPM} = r_{E,CAPM} \times (1 - Lev) + r_D \times Lev \times (1 - Tax)$, $wacc_{FF3} = r_{E,FF3} \times (1 - Lev) + r_D \times Lev \times (1 - Tax)$, and $wacc_{Car} = r_{E,Car} \times (1 - Lev) + r_D \times Lev \times (1 - Tax)$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
I/K	1.00												
$Cash/K$	0.33**	1.00											
$r_{E,CAPM}$	0.14**	0.00	1.00										
$r_{E,FF3}$	0.06**	-0.05**	0.72**	1.00									
$r_{E,Car}$	0.11**	0.00	0.50**	0.66**	1.00								
$r_{E,GGM,HDZ}$	-0.07**	-0.10**	0.09**	0.05**	0.05**	1.00							
r_D	-0.01**	0.04**	0.02**	0.03**	0.03**	0.11**	1.00						
Lev	-0.13**	-0.27**	0.02**	0.12**	0.05**	0.07**	-0.08**	1.00					
Q	0.35**	0.32**	0.02**	-0.09**	-0.01**	-0.38**	0.02**	-0.47**	1.00				
Tax	0.02**	0.15**	0.07**	0.02**	0.04**	0.03**	-0.08**	0.01**	-0.03**	1.00			
$wacc_{CAPM}$	0.15**	0.06**	0.89**	0.63**	0.46**	0.11**	0.34**	-0.24**	0.10**	-0.03**	1.00		
$wacc_{FF3}$	0.07**	0.03**	0.65**	0.88**	0.60**	0.07**	0.35**	-0.18**	0.02**	-0.08**	0.78**	1.00	
$wacc_{Car}$	0.12**	0.06**	0.47**	0.60**	0.92**	0.07**	0.30**	-0.19**	0.07**	-0.04**	0.60**	0.72**	1.00

* $p < 0.05$, ** $p < 0.01$

Table 2.3: I/K: Two-way sorts

The two panels report the two-way sorts results of I/K. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. $wacc = r_E \times (1 - Lev) + r_D \times Lev \times (1 - Tax)$. In each panel, we sort all firm-year observations into 5×5 portfolios by one WACC measure and $Cash/K$. The mean of I/K in each portfolio is reported. The "High-Low" measures the mean differences between the "High" portfolio and "Low" portfolio in each row or column. We test significance of the mean differences. *significant at 5% level. **significant at 1 % level.

	$Cash/K$						
$wacc_{CAPM}$	1(Low)	2	3	4	5(High)	Total	High-Low
1 (Low)	0.093	0.107	0.136	0.161	0.241	0.131	0.148**
2	0.093	0.108	0.137	0.161	0.216	0.133	0.124**
3	0.097	0.108	0.138	0.163	0.227	0.141	0.130**
4	0.093	0.110	0.140	0.167	0.243	0.150	0.150**
5 (High)	0.104	0.115	0.146	0.191	0.304	0.183	0.200**
Total	0.096	0.109	0.139	0.170	0.258	0.147	0.161**
High-Low	0.011**	0.007**	0.010**	0.029**	0.063**	0.052**	

	$Cash/K$						
$wacc_{Car}$	1(Low)	2	3	4	5(High)	Total	High-Low
1 (Low)	0.097	0.107	0.136	0.170	0.257	0.140	0.175**
2	0.090	0.106	0.134	0.161	0.234	0.135	0.133**
3	0.097	0.108	0.137	0.158	0.227	0.138	0.134**
4	0.098	0.113	0.140	0.172	0.251	0.151	0.150**
5 (High)	0.103	0.117	0.152	0.185	0.289	0.174	0.178**
Total	0.097	0.109	0.139	0.170	0.257	0.148	0.160**
High-Low	0.007**	0.010**	0.017**	0.015**	0.032**	0.034**	

* $p < 0.05$, ** $p < 0.01$

Table 2.4: Investment Regressions with WACC

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. $wacc = r_E \times (1 - Lev) + r_D \times Lev \times (1 - Tax)$. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 wacc_{i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the version of cost of equity in the WACC. In columns 1 to 3 we use the contemporaneous measure of WACC and cash flows. The timing is the same as the equation above. In columns 4 to 6 we use one year lagged measure of WACC and cash flows.

	(1) CAPM	(2) FF3	(3) Car	(4) CAPM, t-1	(5) FF3, t-1	(6) Car, t-1
$Cash/K$	0.121***	0.121***	0.121***	0.104***	0.104***	0.104***
	(8.56)	(8.51)	(8.37)	(8.81)	(8.75)	(8.72)
$wacc$	0.037	-0.047**	0.060***	0.136***	0.066***	0.120***
	(1.48)	(-2.35)	(3.57)	(5.21)	(3.28)	(7.45)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Two-way Clustered	Yes	Yes	Yes	Yes	Yes	Yes
N	75900	75663	73584	70580	70380	68549
Adj. R^2	0.339	0.339	0.343	0.329	0.328	0.333

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Decomposing WACC, Step I

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 C^1_{i,t} + +\alpha_3 C^2_{i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

$C^1_{i,t} = (1 - Tax_{i,t}) \times Lev_{i,t} \times r_{D,i,t}$; $C^2_{i,t} = (1 - Lev_{i,t}) \times r_{E,i,t}$. The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the version of cost of equity in the WACC. We estimate the equation above and reports the estimates in columns 1 to 3. In columns 4 to 6 we add Q as a control variable.

	(1) CAPM	(2) FF3	(3) Car	(4) CAPM	(5) FF3	(6) Car
$Cash/K$	0.116***	0.118***	0.116***	0.099***	0.099***	0.098***
	(8.76)	(8.65)	(8.47)	(8.37)	(8.29)	(8.08)
$(1 - Tax) \times Lev \times r_D$	-0.519***	-0.538***	-0.547***	-0.443***	-0.452***	-0.465***
	(-6.76)	(-6.81)	(-6.54)	(-6.56)	(-6.62)	(-6.36)
$(1 - Lev) \times r_E$	0.188***	0.055**	0.129***	0.080***	0.018	0.075***
	(5.81)	(2.30)	(6.75)	(3.36)	(0.93)	(5.11)
Q				0.044***	0.045***	0.044***
				(14.26)	(14.54)	(14.78)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Two-way Clustered	Yes	Yes	Yes	Yes	Yes	Yes
N	75900	75663	73584	75789	75553	73486
Adj. R^2	0.346	0.344	0.350	0.373	0.373	0.377

t statistics in parentheses

* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 2.6: Decomposing WACC, Step II

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 Lev_{i,t} + \alpha_3 r_{D,i,t} + \alpha_4 Tax_{i,t} + \alpha_5 r_{E,i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the version of cost of equity in the WACC. We estimate the equation above and reports the estimates in columns 1 to 3. Then we add Q as a control variable and report the results in columns 4 to 6.

	(1) CAPM	(2) FF3	(3) Car	(4) CAPM	(5) FF3	(6) Car
$Cash/K$	0.112***	0.112***	0.112***	0.100***	0.100***	0.100***
	(8.19)	(8.11)	(7.97)	(7.98)	(7.91)	(7.73)
Lev	-0.188***	-0.191***	-0.187***	0.002	0.004	0.004
	(-6.76)	(-6.74)	(-6.85)	(0.09)	(0.14)	(0.16)
r_D	-0.086***	-0.087***	-0.090***	-0.080***	-0.080***	-0.084***
	(-5.46)	(-5.47)	(-5.39)	(-5.44)	(-5.44)	(-5.34)
Tax	0.019*	0.019**	0.016*	0.021**	0.021**	0.019**
	(1.92)	(1.96)	(1.70)	(2.35)	(2.41)	(2.21)
r_E	0.090***	0.003	0.069***	0.055***	0.008	0.055***
	(4.34)	(0.17)	(5.56)	(3.29)	(0.63)	(5.44)
Q				0.045***	0.046***	0.046***
				(14.58)	(14.84)	(15.24)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Two-way Clustered	Yes	Yes	Yes	Yes	Yes	Yes
N	75900	75663	73584	75789	75553	73486
Adj. R^2	0.347	0.346	0.352	0.372	0.373	0.377

t statistics in parentheses

* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Table 2.7: Firm Size

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 Lev_{i,t} + \alpha_3 r_{D,i,t} + \alpha_4 Tax_{i,t} + \alpha_5 r_{E,i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the version of cost of equity in the WACC. We sort all firm-year observations into five portfolios by firm total assets each year. In columns 1 to 3, we report the estimates using the sample of largest firms. In columns 4 to 6, we report the estimates using the sample of smallest firms.

	Largest Firm Quintile			Smallest Firm Quintile		
	CAPM	FF3	Car	CAPM	FF3	Car
$Cash/K$	0.088***	0.087***	0.085***	0.098***	0.098***	0.098***
	(3.33)	(3.29)	(3.27)	(5.85)	(5.84)	(5.84)
Lev	-0.155***	-0.157***	-0.146***	-0.201***	-0.206***	-0.201***
	(-5.06)	(-5.01)	(-4.79)	(-3.51)	(-3.55)	(-3.46)
r_D	-0.071***	-0.070***	-0.070***	-0.106***	-0.107***	-0.107***
	(-3.17)	(-3.08)	(-3.18)	(-4.78)	(-4.80)	(-4.81)
Tax	0.020**	0.020**	0.018**	0.022	0.023	0.022
	(2.26)	(2.28)	(2.06)	(1.53)	(1.54)	(1.52)
r_E	0.104***	-0.000	0.109***	0.050	-0.035	0.022
	(2.74)	(-0.00)	(5.77)	(1.62)	(-1.25)	(1.23)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Two-way Clustered	Yes	Yes	Yes	Yes	Yes	Yes
N	14733	14733	14733	14777	14777	14777
Adj. R^2	0.506	0.504	0.508	0.264	0.264	0.264

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Across the Decades

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,CAPM}$ is the cost of equity from the CAPM model. $r_{E,FF3}$ is the cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is the cost of equity from the Carhart's four-factor model. We calculate the cost of equity using firm monthly stock returns in previous five years. Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 Lev_{i,t} + \alpha_3 r_{D,i,t} + \alpha_4 Tax_{i,t} + \alpha_5 r_{E,i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the time periods of the regressions.

	70-79			80-89			90-99			00-11		
$Cash/K$	0.277***	0.277***	0.286***	0.216***	0.217***	0.218***	0.094***	0.095***	0.091***	0.050***	0.050***	0.050***
	(14.02)	(14.13)	(16.36)	(9.50)	(9.49)	(9.99)	(6.92)	(7.03)	(6.22)	(5.66)	(5.75)	(5.30)
Lev	-0.000	-0.002	0.010	-0.315***	-0.328***	-0.298***	-0.146***	-0.147***	-0.146***	-0.122***	-0.124***	-0.120***
	(-0.00)	(-0.05)	(0.23)	(-4.78)	(-5.15)	(-4.78)	(-3.28)	(-3.36)	(-3.17)	(-3.24)	(-3.32)	(-3.25)
r_D	-0.630***	-0.629***	-0.622***	-0.281***	-0.281***	-0.287***	-0.084***	-0.083***	-0.078***	-0.020***	-0.020***	-0.018***
	(-12.62)	(-12.69)	(-12.33)	(-6.57)	(-6.55)	(-7.20)	(-7.83)	(-7.57)	(-6.52)	(-3.26)	(-3.28)	(-2.59)
Tax	-0.075***	-0.075***	-0.075***	-0.042**	-0.040**	-0.043***	0.056***	0.062***	0.055***	0.042***	0.039***	0.040***
	(-5.85)	(-5.88)	(-5.97)	(-2.33)	(-2.24)	(-2.58)	(4.90)	(5.72)	(4.91)	(3.51)	(3.47)	(3.71)
$r_{E,CAPM}$	-0.030			0.217***			0.070**			-0.006		
	(-1.04)			(3.02)			(2.07)			(-0.19)		
$r_{E,FF3}$		-0.053**			0.004			0.043			-0.072*	
		(-2.06)			(0.13)			(1.51)			(-1.83)	
$r_{E,Car}$			0.038**			0.129***			0.051***			0.030
			(2.39)			(4.95)			(2.67)			(1.03)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Two-way	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15821	15821	15672	19072	19072	18865	17894	17818	17100	17306	17143	16176
Adj. R^2	0.546	0.546	0.549	0.375	0.374	0.379	0.441	0.443	0.453	0.460	0.462	0.466

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Controlling for Many Macro Factors

This table reports the estimates from the pure time series regressions. See appendix for details of variable construction. We sort all firm-year observations into five portfolios by firm total assets each year. For each accounting variable we take the median of each portfolio. For each portfolio we estimate the following model $\frac{I_t}{K_t} = \alpha_{\beta M} + \alpha_\beta x_{\beta,t} + \alpha_M x_{M,t} + \varepsilon_t$, with $x_{\beta,t} = b'(I - A^\beta \overline{\beta})^{-1} A^\beta (Z_t^\beta - \overline{Z}^\beta)$, and $x_{M,t} = b'(I - A^M \overline{\beta})^{-1} A^M (Z_t^M - \overline{Z}^M)$. b is a vector with the first element equal to one and the other elements equal to zero. Consider the variable φ_t which could be β_t (WACC) or M_t (Cash). A^φ is the coefficient matrix from a vector autoregression (VAR) model $Z_{t+1}^\varphi - \overline{Z}^\varphi = A^\varphi (Z_t^\varphi - \overline{Z}^\varphi) + \sigma_Z^\varphi \varepsilon_{t+1}^\varphi$, with $Z_t^\varphi = \begin{bmatrix} \varphi_t \\ F_t^\varphi \end{bmatrix}$ and a $K \times 1$ vector F_t. We estimate the F_t by three steps. First, we construct a balanced panel with macro time series data and firm time series data (median across all firms each year) from 1955 to 2011. Second, we extract the first n principal components (PCs or factors) of this balanced panel with $n \ll N$ which is the number of time series in the panel. Third, we run OLS regressions with φ_t as the dependent variable and one period lagged factors as independent variables, and use Bayesian information criterion (BIC) to choose which factors to use to forecast φ_t in VAR. We also include all two-factor interactions, and squared factor items as candidates. We search over all possible combinations and find the one (a $K \times 1$ vector F_t with $K \leq n$) that gives the minimum BIC. The t-statistics are adjusted for heteroskedasticity and autocorrelation in error terms by a Newey-West standard error. The first row indicates the portfolio we use.

	(1) Smallest Firm	(2)	(3)	(4)	(5) Largest Firm	Overall
$x_{\beta,t}$	-0.196***	-0.177***	-0.208***	-0.277***	-0.226***	-0.216***
	(-5.70)	(-3.11)	(-4.36)	(-5.02)	(-4.40)	(-4.06)
$x_{M,t}$	0.196**	0.345***	0.305**	0.423***	0.185**	0.373**
	(2.19)	(2.81)	(2.62)	(2.73)	(2.24)	(2.49)
Newey-West Errors	Yes	Yes	Yes	Yes	Yes	Yes
N	57	57	57	57	57	57
Adj. R^2	0.448	0.339	0.383	0.384	0.344	0.354

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Implied Cost of Equity Capital

This table reports the estimates from the panel regressions. The firm accounting data come from the COMPUSTAT/CRSP merged data file. The stock return data are from CRSP. The sample period is from 1955 to 2011. The firm earnings forecasts are from I/B/E/S. The sample period is from 1980 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms with a negative average cash flow. The gross capital stock K is Item PPEGT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. $r_{E,GGM,HDZ}$ is the cost of equity from Gordon Growth Model with model predicted future earnings as in Hou et al. (2011). $r_{E,GLS,HDZ}$ is the cost of equity from Residual Income Model with model predicted future earnings as in Hou et al. (2011). $r_{E,GGM,IBES}$ is the cost of equity from Gordon Growth Model with earnings forecasts from I/B/E/S. $r_{E,GLS,IBES}$ is the cost of equity from Residual Income Model with earnings forecasts from I/B/E/S. $r_{E,CP}$ is the cost of equity from Chava and Purnanandam (2010). Following Frank and Goyal (2009), we construct the firm target leverage ratio Lev. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. r_D is the average cost of debt, which is Item XINT/(Item DLTT + Item DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. The model is

$$\frac{I_{i,t}}{K_{i,t-1}} = \alpha_0 + \alpha_1 \frac{Cash_{i,t}}{K_{i,t-1}} + \alpha_2 Lev_{i,t} + \alpha_3 r_{D,i,t} + \alpha_4 Tax_{i,t} + \alpha_5 r_{E,i,t} + \sum_i firm_i + \sum_t year_t + \varepsilon_{i,t}.$$

The firm and year fixed effects are included. The standard errors are clustered at both firm and year dimensions. The first row indicates the version of cost of equity.

	(1) GGM,HDZ	(2) GLS,HDZ	(3) GGM,IBES	(4) GLS,IBES	(5) CP
$Cash/K$	0.110***	0.126***	0.089***	0.066***	0.102***
	(5.41)	(4.72)	(4.63)	(3.22)	(5.10)
Lev	-0.147***	-0.161***	-0.198***	-0.189***	-0.231***
	(-6.27)	(-5.32)	(-5.31)	(-6.74)	(-6.38)
r_D	-0.087***	-0.101***	-0.045***	-0.055***	-0.053***
	(-6.25)	(-6.35)	(-3.41)	(-3.26)	(-4.38)
Tax	-0.012	-0.018	0.050***	0.006	0.045***
	(-1.21)	(-1.59)	(4.03)	(0.41)	(3.51)
r_E	-0.153***	-0.064***	-0.266***	-0.036	-0.091***
	(-10.35)	(-2.85)	(-6.80)	(-0.91)	(-4.11)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Two-way Clustered	Yes	Yes	Yes	Yes	Yes
N	40256	33205	26794	11903	33796
Adj. R^2	0.402	0.404	0.478	0.527	0.469

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.5: WACC - First Significant Factor

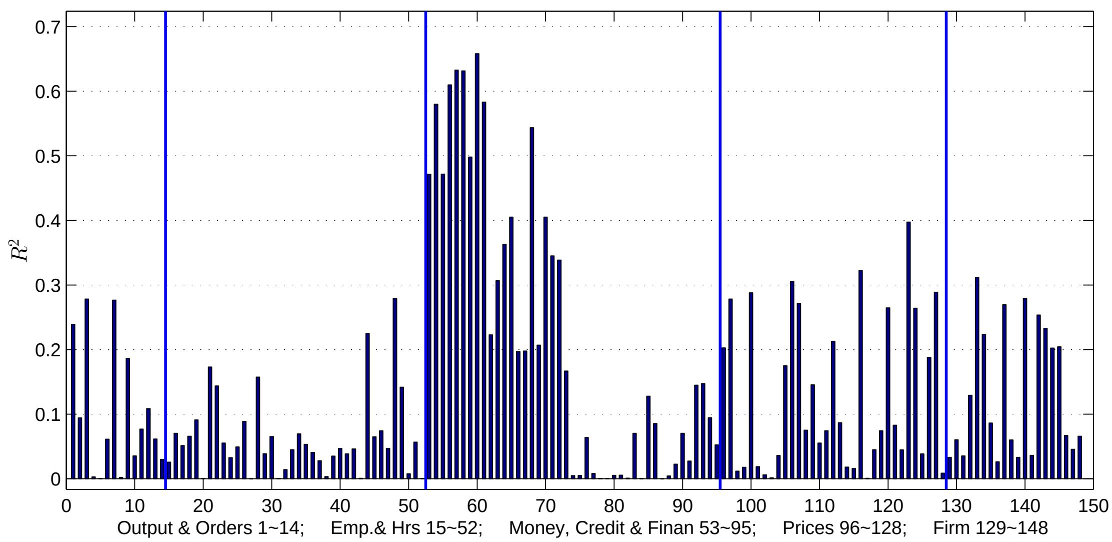

Figure 2.6: WACC - Second Significant Factor

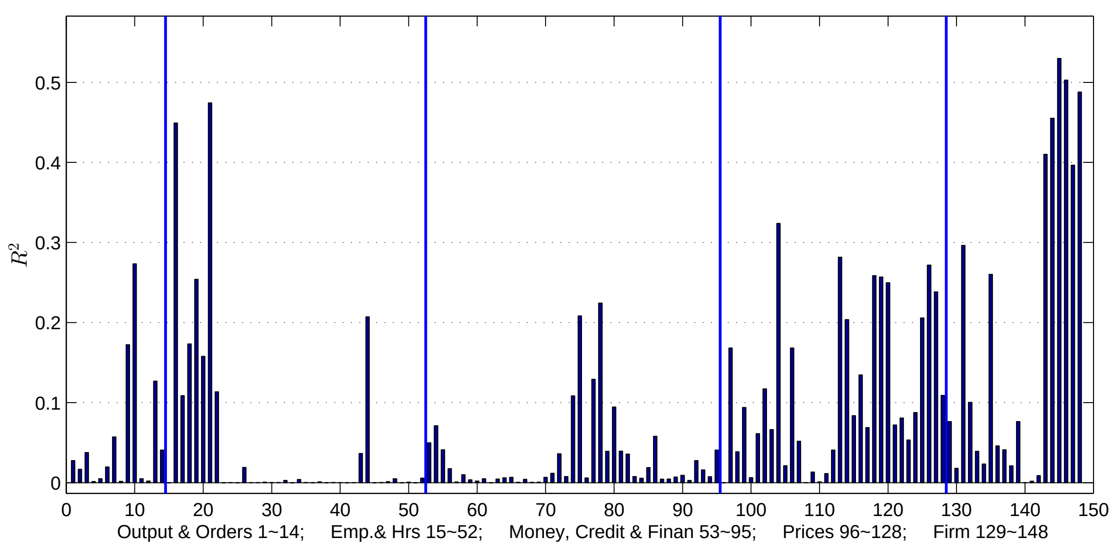

Figure 2.7: WACC - Third Significant Factor

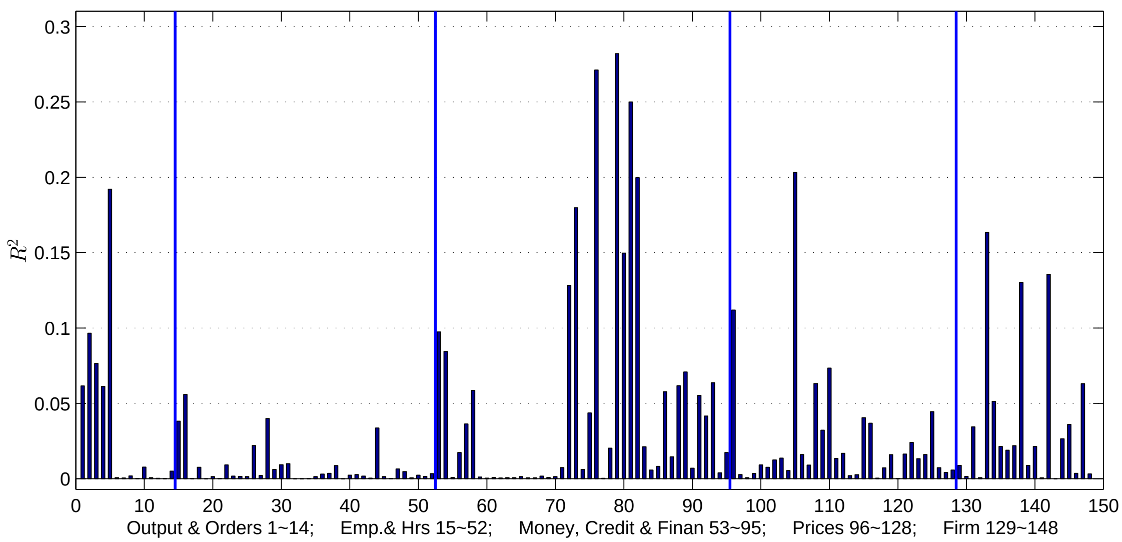

Figure 2.8: Cash - First Significant Factor

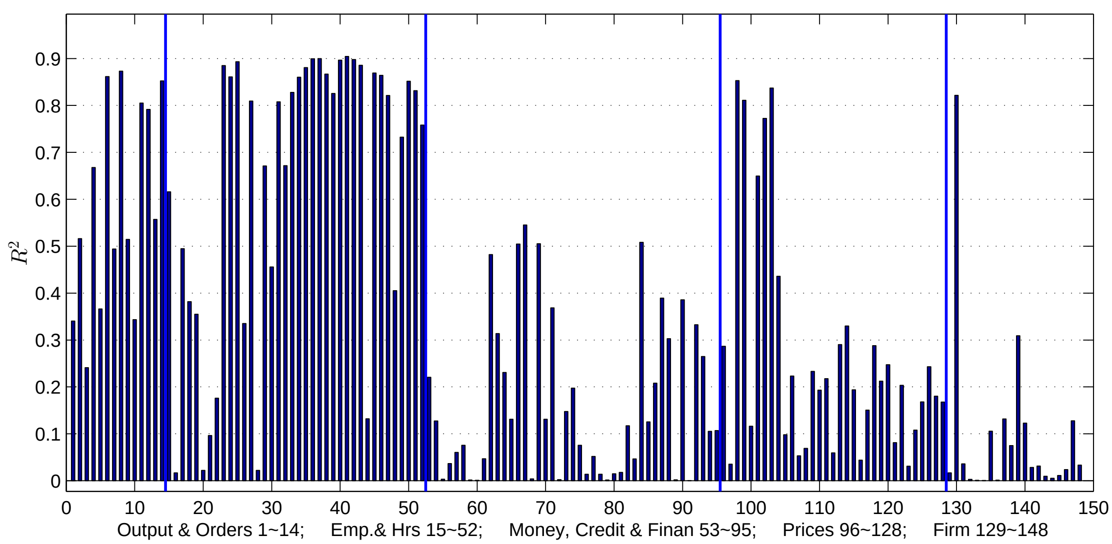

Figure 2.9: Cash - Second Significant Factor

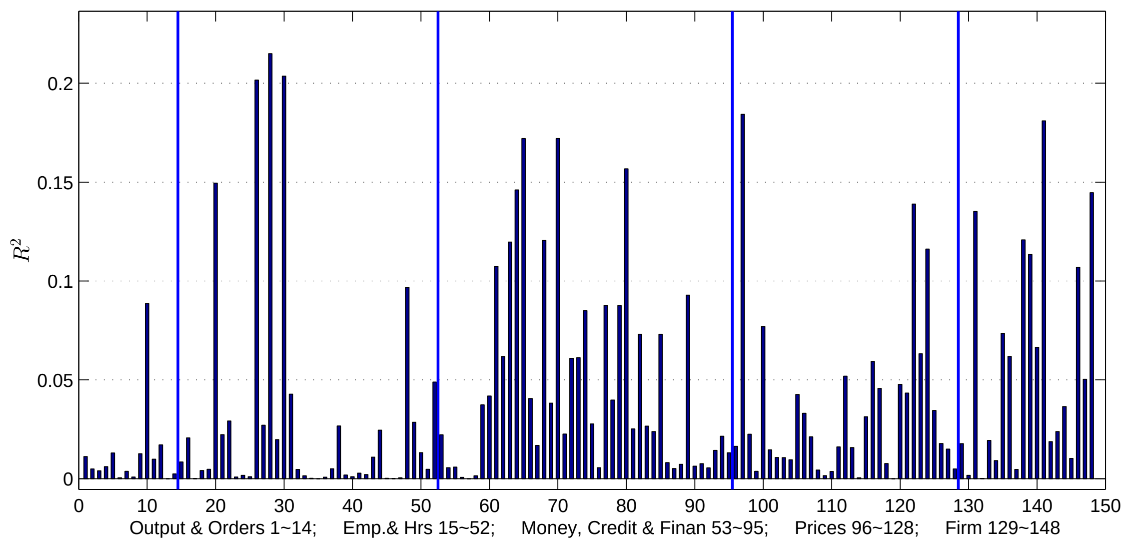

Figure 2.10: Cash - Third Significant Factor

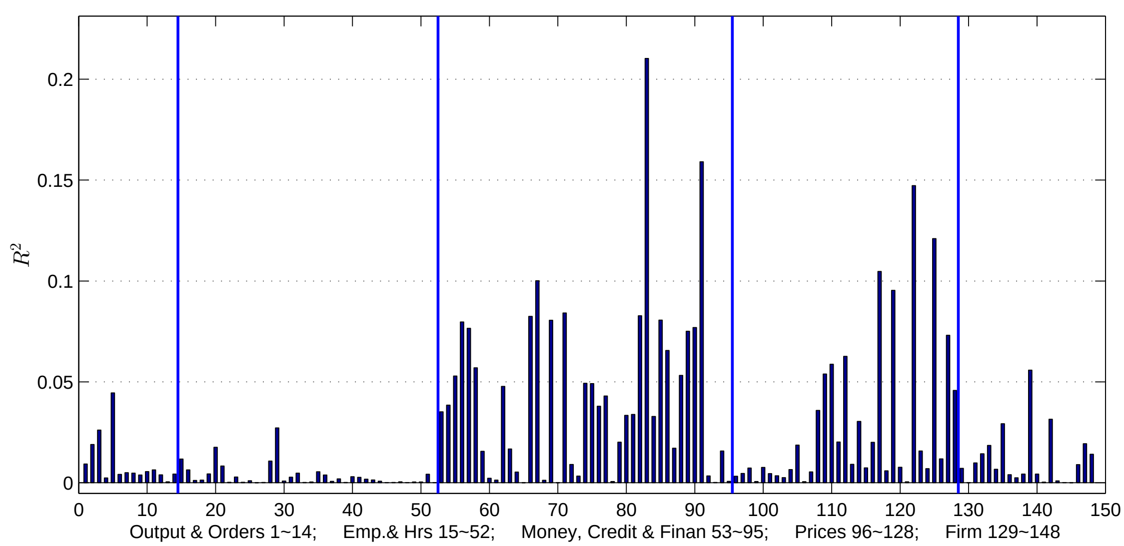

Figure 2.11: Cash - Fourth Significant Factor

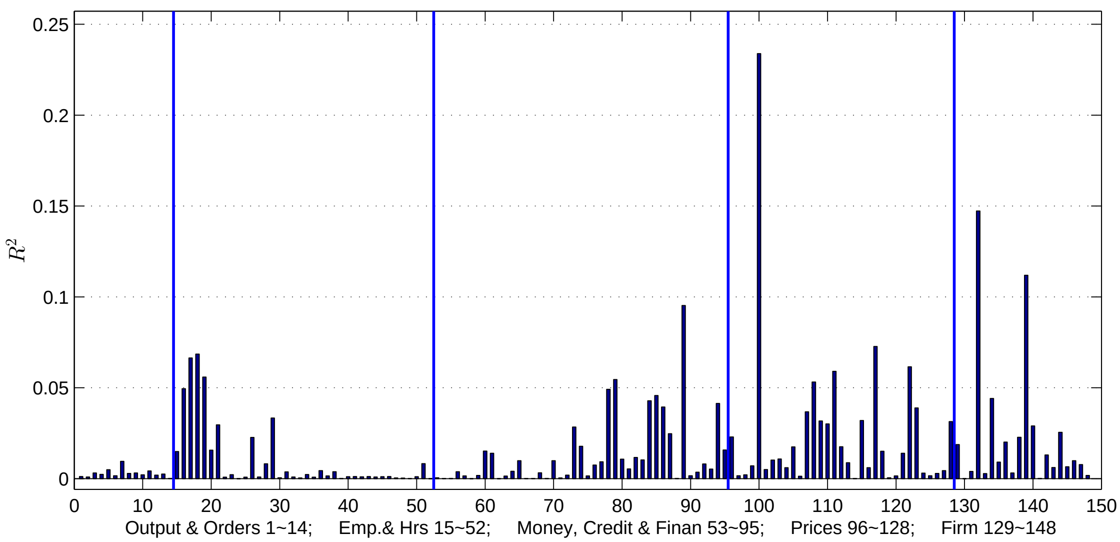

Table 2.11: Macro Data

FD = First Difference; Log FD = Logarithm First Difference; Log SD=Logarithm Second Difference; Group 1 = Output and Orders; Group 2 = Employment and Hours; Group 3 = Money, Credit and Finance; Group 4 = Prices

grp.	No.	description	original name	trans.
1	1	ISM Manufacturing: Production Index	NAPMPI	Level
1	2	ISM Manufacturing: PMI Composite Index	NAPM	Level
1	3	ISM Manufacturing: New Orders Index	NAPMNOI	Level
1	4	ISM Manufacturing: Inventories Index	NAPMII	Level
1	5	ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	Level
1	6	Industrial Production Index	INDPRO	Log FD
1	7	Industrial Production: Durable Consumer Goods	IPDCONGD	Log FD
1	8	Industrial Production: Business Equipment	IPBUSEQ	Log FD
1	9	Industrial Production: Consumer Goods	IPCONGD	Log FD
1	10	Industrial Production: Nondurable Consumer Goods	IPNCONGD	Log FD
1	11	Industrial Production: Materials	IPMAT	Log FD
1	12	Industrial Production: Durable Materials	IPDMAT	Log FD
1	13	Industrial Production: nondurable Materials	IPNMAT	Log FD
1	14	Industrial Production: Final Products (Market Group)	IPFINAL	Log FD
2	15	ISM Manufacturing: Employment Index	NAPMEI	Level
2	16	Average Weekly Hours of Production and Nonsupervisory Employees: Construction	CES2000000007	Level
2	17	Average Weekly Hours of Production and Nonsupervisory Employees: Durable Goods	CES3100000007	Level
2	18	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	CES0600000007	Level

grp.	No.	description	original name	trans.
2	19	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	AWHMAN	Level
2	20	Average Weekly Hours of Production and Nonsupervisory Employees: Mining and Logging	CES1000000007	Level
2	21	Average Weekly Hours of Production and Nonsupervisory Employees: Nondurable Goods	CES3200000007	Level
2	22	Civilian Labor Force Participation Rate	CIVPART	FD
2	23	Unemployment Rate - Men	LNS14000001	FD
2	24	Unemployment Rate - Women	LNS14000002	FD
2	25	Civilian Unemployment Rate	UNRATE	FD
2	26	Average (Mean) Duration of Unemployment	UEMPMEAN	FD
2	27	Of Total Unemployed, Percent Unemployed Less than 5 Weeks	LNS13008397	FD
2	28	Of Total Unemployed, Percent Unemployed 5 to 14 Weeks	LNS13025701	FD
2	29	Of Total Unemployed, Percent Unemployed 15 to 26 Weeks	LNS13025702	FD
2	30	Of Total Unemployed, Percent Unemployed 27 Weeks and Over	LNS13025703	FD
2	31	Persons Unemployed 15 weeks or longer, as a percent of the civilian labor force	U1RATE	FD
2	32	Unemployment Rate - 16 to 17 years	LNS14000086	FD
2	33	Unemployment Rate - 18 to 19 years	LNS14000088	FD
2	34	Unemployment Rate - 20 to 24 years	LNS14000036	FD
2	35	Unemployment Rate - 25 to 34 years	LNS14000089	FD
2	36	Unemployment Rate - 35 to 44 years	LNS14000091	FD
2	37	Unemployment Rate - 45 to 54 years	LNS14000093	FD
2	38	Unemployment Rate - 55 years and over	LNS14024230	FD
2	39	Unemployment Rate - 16 to 19 years	LNS14000012	FD
2	40	Unemployment Rate - 25 to 54 years	LNS14000060	FD
2	41	Unemployment Rate - 25 years and over	LNS14000048	FD
2	42	Unemployment Rate - 20 years and over	LNS14000024	FD

grp.	No.	description	original name	trans.
2	43	United States Employees on Nonfarm Payrolls: Manufacturing	USMANEMPM	Log FD
2	44	Civilian Labor Force	CLF16OV	Log FD
2	45	Unemployed	UNEMPLOY	Log FD
2	46	Unemployment Level - Men	LNS13000001	Log FD
2	47	Unemployment Level - Women	LNS13000002	Log FD
2	48	Civilians Unemployed - Less Than 5 Weeks	UEMPLT5	Log FD
2	49	Civilians Unemployed for 5-14 Weeks	UEMP5TO14	Log FD
2	50	Civilians Unemployed - 15 Weeks & Over	UEMP15OV	Log FD
2	51	Civilians Unemployed for 15-26 Weeks	UEMP15T26	Log FD
2	52	Civilians Unemployed for 27 Weeks and Over	UEMP27OV	Log FD
3	53	Moody's Seasoned Baa Corporate Bond Yield: Difference	DBAA	Level
3	54	Moody's Seasoned Aaa Corporate Bond Yield: Difference	DAAA	Level
3	55	1-Year Treasury Constant Maturity Rate: Difference	DGS1	Level
3	56	3-Year Treasury Constant Maturity Rate: Difference	DGS3	Level
3	57	5-Year Treasury Constant Maturity Rate: Difference	DGS5	Level
3	58	10-Year Treasury Constant Maturity Rate: Difference	DGS10	Level
3	59	3-Month Treasury Bill: Secondary Market Rate: Difference	DTB3MS	Level
3	60	Moody's Seasoned Baa Corporate Bond Yield	BAA	FD
3	61	Moody's Seasoned Aaa Corporate Bond Yield	AAA	FD
3	62	1-Year Treasury Constant Maturity Rate	GS1	FD
3	63	3-Year Treasury Constant Maturity Rate	GS3	FD
3	64	5-Year Treasury Constant Maturity Rate	GS5	FD
3	65	10-Year Treasury Constant Maturity Rate	GS10	FD

grp.	No.	description	original name	trans.
3	66	3-Month Treasury Bill: Secondary Market Rate	TB3MS	FD
3	67	Effective Federal Funds Rate	FEDFUNDS	FD
3	68	State and Local Bonds - Bond Buyer Go 20-Bond Municipal Bond Index	MSLB20	FD
3	69	Interest Rates, Government Securities, Treasury Bills for United States	INTGSTUSM193N	FD
3	70	Interest Rates, Government Securities, Government Bonds for United States	INTGSBUSM193N	FD
3	71	Bank Prime Loan Rate	MPRIME	FD
3	72	S&P 500 Monthly Dividend Yield	SYUSAYM	FD
3	73	S&P 500 Industrials (20)	GSPID	Log FD
3	74	S&P 500 P/E Ratio (As Reported Earnings)	SYUSAPM	Log FD
3	75	Australian Dollars per US Dollar	USDAUD	Log FD
3	76	Japanese Yen per US Dollar	USDJPY	Log FD
3	77	US Dollars per British Pound	GBPUSD	Log FD
3	78	Canada Dollar per US Dollar	USDCAD	Log FD
3	79	Switzerland Francs per US Dollar	USDCHF	Log FD
3	80	USA Dollar Trade Weighted Index	DXYD	Log FD
3	81	Currency Component of M1	CURRSL	Log SD
3	82	St. Louis Adjusted Monetary Base	AMBSL	Log SD
3	83	Bank Credit at All Commercial Banks	LOANINV	Log SD
3	84	Commercial and Industrial Loans at All Commercial Banks	BUSLOANS	Log SD
3	85	Consumer Loans at All Commercial Banks	CONSUMER	Log SD
3	86	Real Estate Loans at All Commercial Banks	REALLN	Log SD
3	87	Treasury and Agency Securities at All Commercial Banks	USGSEC	Log SD
3	88	Securities in Bank Credit at All Commercial Banks	INVEST	Log SD
3	89	Other Securities at All Commercial Banks	OTHSEC	Log SD
3	90	Loans and Leases in Bank Credit, All Commercial Banks	LOANS	Log SD
3	91	Other Loans and Leases, All Commercial Banks	OLLACBM027SBOG	Log SD
3	92	Total Consumer Credit Owned and Securitized, Outstanding	TOTALSL	Log SD

grp.	No.	description	original name	trans.
3	93	Total Nonrevolving Credit Owned and Securitized, Outstanding	NONREVSL	Log SD
3	94	Moody's Commodity Index	MSCID	Log SD
3	95	Dow Jones-AIG Commodity Index	DJCD	Log SD
4	96	ISM Manufacturing: Prices Index	NAPMPRI	Level
4	97	University of Michigan: Consumer Sentiment	UMCSENT	FD
4	98	United States Total Nonfarm Payrolls: All Employees	USPAYEMSM	Log FD
4	99	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Goods-Producing	CES0600000035	Log FD
4	100	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Mining and Logging	CES1000000035	Log FD
4	101	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Construction	CES2000000035	Log FD
4	102	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Manufacturing	CES3000000035	Log FD
4	103	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Durable Goods	CES3100000035	Log FD
4	104	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Nondurable Goods	CES3200000035	Log FD
4	105	S&P 500 Composite Price Index (w/GFD extension)	SXPD	Log FD
4	106	Gross Domestic Product: Implicit Price Deflator	GDPDEF	Log SD
4	107	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	CES2000000008	Log SD
4	108	Average Hourly Earnings of Production and Nonsupervisory Employees: Durable Goods	CES3100000008	Log SD
4	109	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	CES0600000008	Log SD

grp.	No.	description	original name	trans.
4	110	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	CES3000000008	Log SD
4	111	Average Hourly Earnings of Production and Nonsupervisory Employees: Mining and Logging	CES1000000008	Log SD
4	112	Average Hourly Earnings of Production and Nonsupervisory Employees: Nondurable Goods	CES3200000008	Log SD
4	113	Producer Price Index: Finished Goods	PPIFGS	Log SD
4	114	Producer Price Index: Intermediate Materials: Supplies & Components	PPIITM	Log SD
4	115	Producer Price Index: Crude Materials for Further Processing	PPICRM	Log SD
4	116	Producer Price Index: Finished Goods: Capital Equipment	PPICPE	Log SD
4	117	Producer Price Index: Finished Consumer Foods	PPIFCF	Log SD
4	118	Producer Price Index: Finished Consumer Goods	PPIFCG	Log SD
4	119	Producer Price Index: Finished Consumer Goods Excluding Foods	PFCGEF	Log SD
4	120	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	Log SD
4	121	Consumer Price Index for All Urban Consumers: Apparel	CPIAPPSL	Log SD
4	122	Consumer Price Index for All Urban Consumers: Food	CPIUFDSL	Log SD
4	123	Consumer Price Index for All Urban Consumers: Medical Care	CPIMEDSL	Log SD
4	124	Consumer Price Index for All Urban Consumers: Shelter	CUSR0000SAH1	Log SD
4	125	Consumer Price Index for All Urban Consumers: Transportation	CPITRNSL	Log SD
4	126	Consumer Price Index for All Urban Consumers: All items less shelter	CUSR0000SA0L2	Log SD
4	127	Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	Log SD
4	128	West Texas Intermediate Oil Price (US$/Barrel)	WTC	Log SD

grp.	No.	description	original name	trans.

Table 2.12: Firm Level Data

K is the lagged Item PPEGT. Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year.

No.	variable	construction
129	M_t (when predict β_t)	(Item DP + Item IB)/(K×(1-δ)); δ=0.1
129	β_t (when predict M_t)	$1-\delta-R_{E,Car}\times(1-Lev)-Lev\times(1-Tax)\times R_D$; δ=0.1
130	sales growth	the change in Item SALE
131	dividend ratio	(Item DVC + Item DVP)/K
132	cash holing	Item CHE/K
133	market leverage	(Item DLTT + Item DLC)/(Item AT + Item PRCC×Item CSHO - Item SEQ - Item TXDB)
134	book leverage	(Item DLTT + Item DLC)/Item AT
135	firm age	the logarithm of number of years since the first appearance in COMPUSTAT
136	firm size	the logarithm of the Item TA in 2004 dollars
137	investment I/K	Item CAPX/K
138	Q	(Item AT + Item PRCC×Item CSHO - Item SEQ - Item TXDB)/ Item AT
139	cash flow $Cash/K$	(Item DP + Item IB)/K
140	sales	Item SALE/K
141	cost of debt R_D	Item XINT/(Item DLTT + Item DLC)
142	target leverage ratio Lev	see Frank and Goyal (2009)
143	$R_{E,CAPM}$	see appendix
144	$R_{E,FF3}$	see appendix
145	$R_{E,Car}$	see appendix
146	Tax_{Top}	top statutory federal corporate income tax rate
147	Tax_{OLS}	OLS regression predicted tax in Graham and Mills (2008)
148	Tax	Item TXT/Item PI

References

Abel, A.B., 1983, Optimal investment under uncertainty, *The American Economic Review* 73, 228–233.

Abel, A.B., and J.C. Eberly, 1994, A unified model of investment under uncertainty, *The American Economic Review* 84, 1369–1384.

Abel, A.B., and J.C. Eberly, 1997, An exact solution for the investment and value of a firm facing uncertainty, adjustment costs, and irreversibility, *Journal of Economic Dynamics and Control* 21, 831–852.

Abel, A.B., and J.C. Eberly, 2002, Investment and q with fixed costs: An empirical analysis .

Abel, A.B., and J.C. Eberly, 2011, How q and cash flow affect investment without frictions: An analytic explanation, *The Review of Economic Studies* 78, 1179–1200.

Acharya, Viral, Sergei A. Davydenko, and Ilya A. Strebulaev, 2012, Cash holdings and credit risk, *Review of Financial Studies* .

AFP, 2011, Current trends in estimating and applying the cost of capital, *Association for Financial Professionals,* http://www.afponline.org/pub/pdf/Cost_of_Capital_summary.pdf.

Alanis, E., and S. Chava, 2012, Shareholder bargaining power and debt overhang .

Albuquerque, A., 2012, Do growth-option firms use less relative performance evaluation?

Almeida, H., and M. Campello, 2007, Financial constraints, asset tangibility, and corporate investment, *Review of Financial Studies* 20, 1429–1460.

Almeida, H., and T. Philippon, 2007, The risk-adjusted cost of financial distress, *The Journal of Finance* 62, 2557–2586.

Alti, A., 2003, How sensitive is investment to cash flow when financing is frictionless?, *The Journal of Finance* 58, 707–722.

Altman, E.I., and V.M. Kishore, 1996, Almost everything you wanted to know about recoveries on defaulted bonds, *Financial Analysts Journal* 57–64.

Andrew, A.B., and O.J. Blanchard, 1986, The present value of profits and cyclical movements in investments, *Econometrica* 54, 249–273.

Baker, M., and J. Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance* 61, 1645–1680.

Bao, J., J. Pan, and J. Wang, 2011, The illiquidity of corporate bonds, *The Journal of Finance* 66, 911–946.

Barberis, N., and M. Huang, 2007, Stocks as lotteries: The implications of probability weighting for security prices .

Barclay, M., C.W. Smith, and E. Morellec, 2006, On the debt capacity of growth options, *Journal of Business* 79, 37–59.

Benninga, S., 2008, *Financial Modeling, 3rd edition* (MIT Press).

Berk, J. B., R. C. Green, and V. Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Berk, J.B., and P.M. DeMarzo, 2011, *Corporate finance, 2nd edition* (Prentice Hall).

Bernanke, B.S., J. Boivin, and P. Eliasz, 2005, Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach, *Quarterly Journal of Economics* 120, 387–422.

Bohn, J.R., and P.J. Crosbie, 2003, Modeling default risk, *KMV Corporation* .

Bond, S., and J. Van Reenen, 2007, Microeconometric models of investment and employment, *Handbook of econometrics* 6, 4417–4498.

Brealey, R.A., S.C. Myers, and F. Allen, 2006, *Corporate finance, 8th edition* (McGraw-Hill/Irwin).

Cappiello, L., R.F. Engle, and K. Sheppard, 2006, Asymmetric dynamics in the correlations of global equity and bond returns, *Journal of Financial econometrics* 4, 537–572.

Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 57–82.

Carlson, M., A. Fisher, and R. Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Carlson, M., A. Fisher, and R. Giammarino, 2006, Corporate investment and asset price dynamics: Implications for seo event studies and long-run performance, *Journal of Finance* 61, 1009–1034.

Chava, S., and A. Purnanandam, 2010, Is default risk negatively related to stock returns?, *Review of Financial Studies* 23, 2523–2559.

Chen, H., and S. Chen, 2012, Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series, *Journal of Financial Economics* 103, 393–410.

Chen, H.J., and S.J. Chen, 2011, Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series, *Journal of Financial Economics* .

Collin-Dufresne, P., and R.S. Goldstein, 2001, Do credit spreads reflect stationary leverage ratios?, *The Journal of Finance* 56, 1929–1957.

Cummins, J.G., and K.A. Hassett, 1992, The effects of taxation on investment: New evidence from firm level panel data, *National Tax Journal* 45, 243–252.

Cummins, J.G., K.A. Hassett, and S.D. Oliner, 2006, Investment behavior, observable expectations, and internal funds, *The American Economic Review* 96, 796–810.

Damodaran, A., 2002, *Investment valuation: Tools and techniques for determining the value of any asset* (John Wiley & Sons Inc).

Davis, J.L., E.F. Fama, and K.R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Duffee, G.R., 1998, The relation between treasury yields and corporate bond yield spreads, *The Journal of Finance* 53, 2225–2241.

Eberly, J., S. Rebelo, and N. Vincent, 2009, Investment and value: A neoclassical benchmark, *NBER working paper* .

Erickson, T., and T.M. Whited, 2000, Measurement error and the relationship between investment and q, *Journal of Political Economy* 108, 1027–1057.

Fama, E.F., and K.R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, E.F., and K.R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fazzari, S.M., R.G. Hubbard, B.C. Petersen, A.S. Blinder, and J.M. Poterba, 1988, Financing constraints and corporate investment, *Brookings papers on economic activity* 141–206.

Frank, M.Z., and V.K. Goyal, 2009, Capital structure decisions: Which factors are reliably important?, *Financial Management* 38, 1–37.

Gala, V.D., and J. Gomes, 2012, Beyond q: Estimating investment without asset prices .

Gebhardt, W.R., C. Lee, and B. Swaminathan, 2001, Toward an implied cost of capital, *Journal of Accounting Research* 39, 135–176.

Gilchrist, S., and C.P. Himmelberg, 1995, Evidence on the role of cash flow for investment, *Journal of monetary Economics* 36, 541–572.

Gilchrist, S., J. Sim, and E. Zakrajśek, 2010, Uncertainty, Financial Frictions, and Investment Dynamics .

Gilchrist, S., V. Yankov, and E. Zakrajšek, 2009, Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets, *Journal of Monetary Economics* 56, 471–493.

Gilchrist, S., and E. Zakrajsek, 2007, Investment and the cost of capital: New evidence from the corporate bond market.

Gilson, S.C., E.S. Hotchkiss, and R.S. Ruback, 2000, Valuation of bankrupt firms, *Review of Financial Studies* 13, 43.

Goldstein, R., N. Ju, and H. Leland, 2001, An ebit-based model of dynamic capital structure*, *The Journal of Business* 74, 483–512.

Gomes, J., and L. Schmid, 2010, Equilibrium credit spreads and the macroeconomy, in *AFA 2010 Atlanta Meetings Paper*.

Gomes, J.F., 2001, Financing investment, *American Economic Review* 91, 1263–1285.

Graham, J., S.B. Smart, and W.L. Megginson, 2010, *Corporate finance: Linking theory to what companies do* (South-Western Pub).

Graham, J.R., and C.R. Harvey, 2001, The theory and practice of corporate finance: evidence from the field, *Journal of Finance* 60, 187–243.

Graham, J.R., and L.F. Mills, 2008, Using tax return data to simulate corporate marginal tax rates, *Journal of Accounting and Economics* 46, 366–388.

Gurkaynak, R.S., B. Sack, and J.H. Wright, 2007, The US Treasury yield curve: 1961 to the present, *Journal of Monetary Economics* 54, 2291–2304.

Hackbarth, D., J. Miao, and E. Morellec, 2006, Capital structure, credit risk, and macroeconomic conditions, *Journal of Financial Economics* 82, 519–550.

Hadlock, C.J., and J.R. Pierce, 2010, New evidence on measuring financial constraints: moving beyond the kz index, *Review of Financial Studies* 23, 1909–1940.

Hart, Oliver, and John Moore, 1994, A theory of debt based on the inalienability of human capital, *The Quarterly Journal of Economics* 109, 841–79.

Hennessy, C.A., A. Levy, and T.M. Whited, 2007, Testing q theory with financing frictions, *Journal of Financial Economics* 83, 691–717.

Hong, G., and A. Warga, 2000, An empirical study of bond market transactions, *Financial Analysts Journal* 32–46.

Hou, K., M.A. Van Dijk, and Y. Zhang, 2011, The implied cost of capital: A new approach, *Journal of Accounting and Economics* .

Hubbard, R.G., 1998, Capital-market imperfections and investment, *Journal of economic literature* 36, 193–225.

Kaplan, S. N., and R. S. Ruback, 1995, The valuation of cash flow forecasts: An empirical analysis, *Journal of Finance* 50, 1059–1093.

Kaplan, S.N., and L. Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *The Quarterly Journal of Economics* 112, 169–215.

Koller, T., M. Goedhart, and D. Wessels, 2010, *Valuation: measuring and managing the value of companies* (John Wiley & Sons Inc).

Lamont, O., C. Polk, and J. Saá-Requejo, 2001, Financial constraints and stock returns, *Review of Financial Studies* 14, 529–554.

Lee, C.M.C., E.C. So, and C.C.Y. Wang, 2010, Evaluating implied cost of capital estimates, *Working Paper, SSRN* .

Leland, H.E., 1998, Agency costs, risk management, and capital structure, *The Journal of Finance* 53, 1213–1243.

Lewellen, J., 2010, Accounting anomalies and fundamental analysis: An alternative view, *Journal of Accounting and Economics* .

Lin, X., and L. Zhang, 2013, The investment manifesto, *Journal of Monetary Economics* .

Liu, L.X., T.M. Whited, and L. Zhang, 2009, Investment-based expected stock returns, *Journal of Political Economy* 117, 1105–1139.

Ludvigson, S.C., and S. Ng, 2009, Macro factors in bond risk premia, *Review of Financial Studies* 22, 5027–5067.

Merton, R.C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of finance* 29, 449–470.

Miao, J., and P. Wang, 2010, Credit Risk and Business Cycles .

Moyen, N., 2005, Investment–cash flow sensitivities: Constrained versus unconstrained firms, *The Journal of finance* 59, 2061–2092.

Myers, S.C., 1974, Interactions of corporate financing and investment decisions-implications for capital budgeting, *Journal of Finance* 29, 1–25.

Myers, S.C., 1977, Determinants of corporate borrowing, *Journal of financial economics* 5, 147–175.

Nekrasov, A., and P. Shroff, 2009, Fundamentals-based risk measurement in valuation, *The Accounting Review* 84, 1983–2011.

Ozdagli, A., 2012, Financial leverage, corporate investment and stock returns, *Review of Financial Studies* 25, 1033–1069.

Pastor, L., M. Sinha, and B. Swaminathan, 2008, Estimating the intertemporal risk–return tradeoff using the implied cost of capital, *Journal of Finance* 63, 2859–2897.

Pastor, L., and P. Veronesi, 2005, Rational ipo waves, *Journal of Finance* 60, 1713–1757.

Petersen, M.A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of financial studies* 22, 435–480.

Philippon, T., 2009, The Bond Market's q, *Quarterly Journal of Economics* 124, 1011–1056.

Ross, S.A., R.W. Westerfield, and J.F. Jaffe, 2008, *Corporate finance, 8th edition* (McGraw-Hill, Irwin).

Schultz, P., 2001, Corporate bond trading costs: A peek behind the curtain, *The Journal of Finance* 56, 677–698.

Stambaugh, R.F., J. Yu, and Y. Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 288–302.

Stiglitz, J.E., and A. Weiss, 1981, Credit rationing in markets with imperfect information, *The American economic review* 393–410.

Stock, J.H., and M. Watson, 2012, Generalized shrinkage methods for forecasting using many predictors, *Journal of Business and Economic Statistics* 30, 481–493.

Vassalou, M., and Y. Xing, 2004, Default risk in equity returns, *The Journal of Finance* 59, 831–868.

Welch, I., 2004, Capital structure and stock returns, *Journal of Political Economy* 112, 106–132.

Whited, T.M., 1994, Problems with identifying adjustment costs from regressions of investment on q, *Economics Letters* 46, 327–332.

Whited, T.M., and G. Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531–559.

Zhang, L., 2005, The value premium, *Journal of Finance* 60, 67–103.

Appendix A

A.1 Proof

$$log(I) \approx \Gamma + \frac{(n-1)\theta}{\gamma_-} log(CDS) - \frac{(n-1)\theta}{\gamma_-} log(y+m)(r+m)$$

with $\gamma_- = 0.5 - \frac{\mu}{\sigma^2} - \sqrt{(0.5 - \frac{\mu}{\sigma^2})^2 + \frac{2(r+m)}{\sigma^2}}$, $\Gamma = log\left[\beta\left(\frac{n-1}{n\gamma}\right)\left(\frac{c+m}{\frac{c+m}{r+m} - \frac{\beta}{\psi}}\right)^{\frac{\theta}{\gamma_-}}\right]^{n-1}$, and $n = \{2, 4, 6...\}$.

We want to show the investment is more sensitive to credit spreads for firms with low growth and high volatility, and bonds with longer maturity. It is equivalent to show that $\partial|\frac{1}{\gamma_-}|/\partial\mu < 0$, $\partial|\frac{1}{\gamma_-}|/\partial\sigma^2 > 0$, and $\partial|\frac{1}{\gamma_-}|/\partial m < 0$.

First, let $X = 0.5 - \frac{\mu}{\sigma^2}$ and $C = \frac{2(r+m)}{\sigma^2}$. It immediately follows that $\frac{\partial X}{\partial \mu} < 0$, and $\frac{\partial \gamma_-}{\partial X} = 1 - \frac{1}{\sqrt{1+\frac{C}{X}}}$. Since $\sqrt{1 + \frac{C}{X}} > \sqrt{1} = 1$, we have $\frac{\partial \gamma_-}{\partial X} > 0$. So $\frac{\partial \gamma_-}{\partial \mu} = \frac{\partial \gamma_-}{\partial X}\frac{\partial X}{\partial \mu} < 0$, $\frac{\partial |\gamma_-|}{\partial \mu} = -\frac{\partial \gamma_-}{\partial \mu} > 0$, and $\frac{\partial |\frac{1}{\gamma_-}|}{\partial \mu} < 0$.

Second, let $X = 0.5 - \frac{\mu}{\sigma^2}$, and $Y = \frac{2(r+m)}{\sigma^2}$. It immediately follows that $\frac{\partial X}{\partial \sigma^2} > 0$, $\frac{\partial Y}{\partial \sigma^2} < 0$, and $\frac{\partial \gamma_-}{\partial Y} = -\frac{1}{\sqrt{X^2+Y}} < 0$. So $\frac{\partial \gamma_-}{\partial Y}\frac{\partial Y}{\partial \sigma^2} > 0$. We have shown $\frac{\partial \gamma_-}{\partial X} > 0$, so $\frac{\partial \gamma_-}{\partial X}\frac{\partial X}{\partial \sigma^2} > 0$. $\frac{\partial \gamma_-}{\partial \sigma^2} = \frac{\partial \gamma_-}{\partial X}\frac{\partial X}{\partial \sigma^2} + \frac{\partial \gamma_-}{\partial Y}\frac{\partial Y}{\partial \sigma^2} > 0$ and $\frac{\partial |\frac{1}{\gamma_-}|}{\partial \sigma^2} > 0$.

Third, let $Y = \frac{2(r+m)}{\sigma^2}$. We have $\frac{\partial Y}{\partial m} > 0$. $\frac{\partial \gamma_-}{\partial m} = \frac{\partial \gamma_-}{\partial Y}\frac{\partial Y}{\partial m} < 0$, and $\frac{\partial |\frac{1}{\gamma_-}|}{\partial m} < 0$.

A.2 Distance to Default

KMV-Merton model

The total firm value V satisfies the following equation under the physical measure:

$$\frac{dV}{V} = \mu_V dt + \sigma_V dW^P$$

The firm issues a single discount bond with a face value D with time to maturity $\tau = T - t$. T is the mature time and t is the current time. On the mature time T, if the total firm value is below D, then the debt holders take over the firm. Otherwise, the equity holders pay the face value. The time t expected default probability at time T under physical measure is

$$E_t^P(\mathbb{I}_{V(T)<D}) = \pi^P(V(T) < D|V(t))$$

$$= \pi^P(V(t)e^{(\mu_V - \frac{1}{2}\sigma_V^2)\tau + \sigma_V(W_T^P - W_t^P)} < D|V(t))$$

$$= \pi^P(\frac{W_T^P - W_t^P}{\sqrt{\tau}} < -\frac{ln(V(t)/D) + (\mu_V - \frac{1}{2}\sigma_V^2)\tau}{\sigma_V\sqrt{\tau}}|V(t))$$

$$= N(-DD)$$

where

$$DD = \frac{ln(V(t)/D) + (\mu_V - \frac{1}{2}\sigma_V^2)\tau}{\sigma_V\sqrt{\tau}}$$

.

To calculate DD, we need μ_V, σ_V and V, all of which are not directly observable. We need to recover those values from historical equity prices. Under risk neutral measure, assuming the total firm value is a tradable asset, then we have:

$$\frac{dV}{V} = rdt + \sigma_V dW^Q$$

The market value of non-dividend-paying stock is $S(V,\tau)$, satisfying the following equation when $\tau > 0$:

$$E^Q(\frac{dS}{S}) = rdt$$

where $dS = S_V dV - S_\tau dt + \frac{1}{2} S_{VV} dV^2$. It implies the following differential equation:

$$S_V rV - S_\tau + \frac{1}{2} S_{VV} V^2 \sigma_V^2 - rS = 0$$

Subject to $S[V,0] = max[0, V(T) - D]$ when $\tau = 0$. These two equations are identical to the dynamic of an European call option on a non-dividend-paying stock with strike price D and stock price V. The value of the equity is then

$$S = V\phi(d_1) - e^{-r\tau} D\phi(d_2) \tag{A.1}$$

with $d_1 = \frac{ln(V/D)+(r+0.5\sigma_V^2)\tau}{\sigma_V\sqrt{\tau}}$ and $d_2 = d_1 - \sigma_V\sqrt{\tau}$

W can write the dynamic of S in the form $\frac{dS}{S} = rdt + \sigma_E dW^Q$. On the other hand, we have

$$dS = S_V dV - S_\tau dt + \frac{1}{2} S_{VV} dV^2 = (S_V V r - S_\tau + \frac{1}{2} S_{VV} V^2 \sigma_V^2)dt + S_V V \sigma_V dW^Q$$

So

$$rS = S_V V r - S_\tau + \frac{1}{2} S_{VV} V^2 \sigma_V^2$$

and

$$S\sigma_E = S_V V \sigma_V$$

We can estimate σ_V using σ_E which is observable. I claim $S_V = \phi(d_1)$. Since $S_V = \phi(d_1) + \phi_V(d_1)V - e^{-r\tau} D\phi_V(d_2)$, I need to show $\phi_V(d_1)V - e^{-r\tau} D\phi_V(d_2) = 0$. Because

$$\phi_V(d_1)V = \frac{1}{\sqrt{2\pi}\sigma_V\sqrt{\tau}} exp[-\frac{ln^2(V/D) + (r+0.5\sigma_V^2)^2\tau^2 + 2ln(V/D)(r+0.5\sigma_V^2)\tau}{2\sigma_V^2\tau}],$$

and

$$e^{-r\tau}D\phi_V(d_2) = \frac{e^{-r\tau}D}{\sqrt{2\pi}V\sigma_V\sqrt{\tau}}exp[-\frac{ln^2(V/D)+(r-0.5\sigma_V^2)^2\tau^2+2ln(V/D)(r-0.5\sigma_V^2)\tau}{2\sigma_V^2\tau}],$$

we have $(r-0.5\sigma_V^2)^2\tau^2 + 2ln(V/D)(r-0.5\sigma_V^2)\tau + 2r\sigma_V^2\tau^2 + 2\sigma_V^2\tau ln(V/D) = (r+0.5\sigma_V^2)^2\tau^2 + 2ln(V/D)(r+0.5\sigma_V^2)\tau$. Hence $e^{-r\tau}D\phi_V(d_2) = \phi_V(d_1)V$. So

$$\sigma_E = \frac{V}{S}\phi(d_1)\sigma_V. \tag{A.2}$$

We can solve the nonlinear equation (A.1) and (A.2) for σ_V and V. S is the daily equity value. It is common to set T=1. r is the daily 1-year constant-maturity Treasury yields. I use 250-day moving window to estimate σ_E using daily stock returns. D is equal to the sum of the firm's current liabilities and one-half of the its long run liabilities. Both liability data are using quarter COMPUSTAT and interpolated to daily frequency.

Bohn and Crosbie (2003) explain that "In practice the market leverage moves around far too much for [Equation (2)] to provide reasonable results." To resolve this problem, I follow Bohn and Crosbie (2003) and Vassalou and Xing (2004) by implementing a complicated iterative procedure.

At the end of each month, the initial value of σ_V is $\sigma_V^{(0)} = \frac{S}{S+D}\sigma_E$. With this initial value, I infer V every day for the previous 250-day using equation (A.1). With the daily V, I calculate the new estimate for $\sigma_V^{(1)}$, until $|\sigma_V^{(n)} - \sigma_V^{(n-1)}| < 10^{-3}$. Then I use $\sigma_V^{(n)}$ to calculate the V and infer the μ_V.

A.3 Cost of Equity Proxies

Stock Return Based Methods

$r_{E,CAPM}$ is the cost of equity from the CAPM model, $r_{E,CAPM} = r_f + \beta E(r_M - r_f)$. The risk free rate r_f is 10-year Treasury yield from FRED. To estimate firm β, we run rolling window regressions using previous five years monthly stock returns. The dependent variable is the excess stock return (stock return from CRSP - risk free rate in Fama-French market excess return factor) and the independent variable is the Fama-French market excess return.[1] $E(r_M - r_f)$ is the historical mean of the Fama-French market excess return, i.e. the date t equity premium is the average of Fama-French market excess return from time t to the time 1. $r_{E,FF3}$ is cost of equity from the Fama-French three-factor model. $r_{E,Car}$ is cost of equity from the Carhart four-factor model. Both of them are constructed in the same way as $r_{E,CAPM}$.

Implied Cost of Capital

We contruct two types of earnings forecasts. The first is IBES-based earnings forecasts which are from I/B/E/S. The sample period is from 1980 to 2011. The earnings forecasts range from one to five years, and a long term growth rate is provided for some firms. We use the median of earnings forecasts. The second is the model predicted earnings. Hou et al. (2011) (HDZ), and Lee et al. (2010) have found a fairly simple model to predict earnings that seems to do rather well, and so we use that as well. The model is $E_{j,t+\Delta t} = \alpha_0 + \alpha_1 EV_{j,t} + \alpha_2 TA_{j,t} + \alpha_3 DIV_{j,t} + \alpha_4 DD_{j,t} + \alpha_5 E_{j,t} + \alpha_6 NegE_{j,t} + \alpha_7 ACC_{j,t} + \varepsilon_{j,t+\Delta t}$.

[1]Downloaded from French's webpage: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/F-F_Research_Data_Factors.zip

Both papers estimate this model using pooled cross-section regressions using a rolling prior ten years of data for each year. For comparability we do the same. Δt ranges from 1 to 5. E is the earnings before extraordinary items (Item IB); EV is the enterprise value which is total asset (Item AT) + market value of equity (Item PRCC$\times$Item CSHO) - book value of equity; TA is total assets (Item AT); DIV is the dividend payment (Item DVT); DD is the dummy for paying dividends; $NegE$ is the dummy for negative earnings (Item IB<0); ACC is total accruals which are change in current assets (Item ACT) + change in debt in current liability (Item DLC) - change in cash and short term investment (Item CHE) - change in current liabilities (Item LCT) - depreciation (Item DP).

We use two accounting models to calculate the cost of equity. The first is Gordon Growth Model (GGM) and the second is Residual Income Model (GLS). Following Lee et al. (2010), $r_{E,GGM,IBES}$ is the cost of equity from GGM with IBES-based earnings per share forecast. We numerically solve the following equation:

$$P_t = \sum_{i=1}^{4} \frac{DPS_{t+i}}{(1 + r_{E,GGM,IBES})^i} + \frac{EPS_{t+5}}{r_e(1 + r_{E,GGM,IBES})^4}$$

with,

$$DPS_{t+1} = EPS_{t+1} \times \kappa$$

where dividend payout ratio: κ follows Hou et al. (2011) and Gebhardt et al. (2001)(GLS): if earnings are positive, κ is the current dividends divided by current earnings; if earnings are negative, κ is the current dividends divided by $0.06\times$ Item TA.

$r_{E,GLS,IBES}$ is the cost of equity from the Residual Income Model (GLS) with IBES-based earnings forecasts. We follow Gebhardt et al. (2001) and Hou et al.

(2011), and solve the following equation:

$$M_t = B_t + \sum_{i=1}^{11} \frac{E_t[(ROE_{t+i} - r_e) \times B_{t+i-1}]}{(1 + r_{E,GLS,IBES})^i} + \frac{E_t[(ROE_{t+12} - r_e) \times B_{t+11}]}{r_{E,GLS,IBES}(1 + r_{E,GLS,IBES})^{11}}$$

where M_t is the market value of equity, B_t is the book value of equity. Book value of equity follows Davis et al. (2000). Particularly, book value of equity=stockholder equity (Item SEQ) + deferred taxes (Item TXDB) + investment tax credit (Item ITCB) - book value of preferred stock; book value of preferred stock=in order: redemption (Item PSTKRV), liquidation (Item PSKTL), or par value of preferred stock (Item PSTK); if stockholder equity is not available, then stockholder equity=book value of common equity (Item CEQ) + par value of preferred stock, or stockholder equity=book value of total assets (Item AT) - book value of total liability (Item LT). The book value of equity evolves according to

$$B_{t+i} = B_{t+i-1} + Earning_{t+i}(1 - \kappa)$$

where B_t and κ are defined the same as before, and $Earning_t$ is from IBES. Return on equity ROE_{t+i} is defined as the following: from year one to year three it is the $\frac{Earning_{t+i}}{B_{t+i-1}}$; through year four to year twelve, it is the interpolated value between ROE_{t+3} and industrial median at time t. Industrial median excludes firms with negative earnings.

$r_{E,GMM,HDZ}$ and $r_{E,GLS,HDZ}$ are constructed in the same way, and we use model predicted earnings to replace IBES-based earnings forecasts.

We also follow the method of implied cost of capital in Chava and Purnanandam (2010) and construct the cost of equity $r_{E,CP}$.

A.4 Variables in Factor-Augmented Vector Autoregressive (FAVAR)

We construct a balanced panel which consists of 148 annual frequent time series from 1955 to 2011. There are 128 macroeconomic time series which are from FRED and Global Financial Data. The details of variable names, description, and data transformation are in Table 2.11. There are 20 firm-level time series. We take the median of the variables across all firms in each year. The details of variable names and construction are in Table 2.12.

A.5 Variable Definition: Chapter One

The firm level accounting information is from the COMPUSTAT North America annual data file. The sample period is from 1980 to 2011. We drop the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000, as they are regulated, financial or public service firms. To make sure the results are not driven by small firms, we drop the firms with total asset below 10 million dollars (inflation adjusted in year 2004 dollars). We also drop the firm with missing value in investment (Item CAPXV) or capital stock (Item PPEGT), and firms with negative market to book ratio.

Total debt is the sum of Item DLC and Item DLTT. Total book value of asset is Item AT. Market value of asset is (Item AT+Item PRCC×Item CSHO-Item CEQ-Item TXDB). Book leverage is the total debt divided by book value of asset; market leverage is the total debt divided by market value of asset; investment is the ratio of capital expenditures (Item CAPXV) to beginning-of-period capital stock (lagged Item PPEGT); Q is the market value of assets divided by the book value of assets; cash flow is earnings before extraordinary items and depreciation (Item IB + Item DP) divided by the beginning-of-period capital stock; payout ratio is the sum of Item DVC, Item DVP and Item PRSTKC divided by Item OIBDP; equity issuance is Item SSTK divided by Item AT; sale is Item SALE; cash holding is Item CHE; profitability is Item OIBDP; R&D is Item XRD. Sale, cash holding, profitability, and R&D are scaled by the beginning-of-period capital stock. Following Almeida and Campello (2007), tangibility is 0.715×Item RECT+0.547×Item INVT+0.535×Item PPENT+Item CHE, scaled by Item AT. The measure of competition is the Herfindahl-Hirschman index (HHI). It is defined as $HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2$, where s_{ijt} is the market share of firm i in industry j (three-digit SIC codes) in year t. A higher HHI implies weaker competition. All variables are winsorized at 1% level each tail every year.

Firm rating is S&P Long-Term Domestic Issuer Credit Rating. This item represents the current rating assigned to the company by Standard & Poor's. The numeric value is 2 (AAA), 4 (AA+), 5 (AA), 6 (AA-), 7 (A+), 8 (A), 9 (A-), 10 (BBB+), 11 (BBB), 12 (BBB-), 13 (BB+), 14 (BB), 15 (BB-), 16 (B+), 17 (B), 18 (B-), 19 (CCC+), 20 (CCC), 21 (CCC-), 23 (CC), and 27 (D).

Volatility is the annualized monthly stock return volatility from CRSP. I calculate the standard deviation in month t using the previous 36 month (month t to month t-35) stock returns, and require at least 24 month non-missing data.

Three popular indices that gauge the extent of financial constraint are employed.

SA index. Following Hadlock and Pierce (2010), SA index = $-0.737\times$Size + 0.043 × $Size^2$ - 0.040 × Age where Size is the log of inflation adjusted (in 2004 dollars) book assets, and age is the number of years the firm has been on COMPUSTAT. When calculating this index, I replace Size with log($4.5 billion) and age with thirty-seven years if the actual values exceed these thresholds.

KZ index. Following Lamont et al. (2001), KZ index = $-1.001909\times$[(Item IB+Item DP)/Item PPENT]+0.2826389×Q + 3.139193×[(Item DLTT + Item DLC)/(Item DLTT + Item DLC + Item SEQ)] - 39.3678×[(Item DVC + Item DVP)/Item PPENT] - 1.314759×[Item CHE/Item PPENT]. Data Item PPENT is lagged.

WW index. Following Whited and Wu (2006), WW index = $-0.091\times$CF - 0.062×DIVPOS + 0.021×TLTD - 0.044×LNTA + 0.102×ISG - 0.035×SG where CF = [(Item IB+Item DP)/Item PPENT]; DIVPOS = 1 if Item DV$>$ 0; $TLTD$ = [(Item DLTT + Item DLC)/(Item DLTT + Item DLC + Item SEQ)]; $LNTA$ = log(Item AT); ISG is the firm's three-digit industry sales growth; SG is the firm's sales growth. Data Item PPENT is lagged.

Item names refer to COMPUSTAT annual data items.

A.6 Variable Definition: Chapter Two

The firm accounting variables come from the COMPUSTAT/CRSP merged data file. The stock returns are from CRSP. The sample period is from 1955 to 2011. We drop foreign companies, and the companies with a SIC code that is between 4900 and 4999, between 6000 and 6999, or greater 9000. We also drop the firms that on average have a negative cash flow. The gross capital stock K is Item PPEGT. Q is (Item AT + Item PRCC×Item CSHO - Item SEQ - Item TXDB)/ Item AT. Cash is the sum of Item DP and Item IB. Capital expenditure I is Item CAPX. Data Item PPEGT is lagged. Tax is the corporate average tax rate, which is Item TXT/ Item PI. We set this value to missing if it is above one or below zero. $r_D$is the average cost of debt, which is Item XINT/(Item DLTT + Item

DLC). Item names refer to COMPUSTAT annual data items. All variables are winsorized at 1% level on each tail every year. Following Frank and Goyal (2009) Table V column 9, we construct the firm target leverage ratio *Lev*.