Essays on the Cross-section of Returns

Dissertation

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Abstract

This dissertation examines what factors determine the cross-section of returns. It contains three chapters.

Chapter 1 investigates whether uncertainty shocks can explain the value premium puzzle. Intuitively, the value of growth options increases when uncertainty is high. As a result, growth stocks hedge against uncertainty risk and earn lower risk premiums than value stocks. An investment-based asset pricing model augmented with time-varying uncertainty accounts for both the value premium and the empirical failure of the capital asset pricing model (CAPM). This study also shows that uncertainty shocks influence cross-sectional investment. Uncertainty has a negative impact on the investment of value firms, while it has a positive impact on the investment of growth firms.

Chapter 2 shows that uncertainty shocks can explain the negative relation between idiosyncratic volatility and expected returns in Ang, Hodrick, Xing and Zhang (2006, 2009). The main intuition is that idiosyncratic volatility amplifies the positive impact of uncertainty shocks on the value of growth options. Therefore, everything else being equal, growth stocks with higher idiosyncratic volatilities perform better than growth stocks with lower idiosyncratic volatilities when uncertainty is high, and consequently have lower expected returns. Using an investment-based asset pricing model with time-varying uncertainty, I show that the idiosyncratic volatility puzzle

exists only in stocks with low book-to-market ratios (growth stocks). The spread in loadings on uncertainty shocks can explain why growth stocks with high idiosyncratic volatilities earn lower average returns than those with low idiosyncratic volatilities.

In Chapter 3, co-authored with Kewei Hou, Chen Xue, and Lu Zhang, we hand-collect data on total assets and earnings from Moody's Industrial Manual to extend the sample for the q-factors back to 1926. We also compare the q-factor model with the Carhart (1997) model in capturing anomalies in the long sample.

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Chapter 1: The Impact of Uncertainty Shocks on the Cross-section of Returns

1.1 Introduction

Time-varying uncertainty, proxied by volatility in stock returns or macro variables, plays an important role in explaining cross-sectional returns. Ang, Hodrick, Xing, and Zhang (2006) and Adrian and Rosenberg (2008) show that market volatility is a significant cross-sectional asset pricing factor. Campbell, Giglio, Polk, and Turley (2012) extend an intertemporal capital asset pricing model (ICAPM) by allowing for stochastic volatility and find that volatility news explains cross-sectional returns. Bansal, Kiku, Shaliastovich, and Yaron (2014) and Segal, Shaliastovich and Yaron (2014) explore the effects of stochastic volatility in the long-run risk model. These studies find that some assets tend to have higher risk loadings on the uncertainty factor, and consequently, show that this factor contributes to explaining the return spread across assets. However, they do not provide the theoretical mechanism for why assets tend to react differentially to the uncertainty factor.

This paper shows that, based on a structural model, time-varying uncertainty can explain the value premium puzzle. Historically, stocks with high book-to-market ratios (value stocks) tend to earn higher average returns than those with low book-to-market ratios (growth stocks); however, the value premium cannot be explained by the capital asset pricing model (CAPM). Figure 1.1 represents the average excess returns of 10 book-to-market sorted portfolios and their expected returns as predicted by the CAPM. It shows that average excess returns rise from the growth portfolio to the value portfolio while the CAPM betas are almost the same for all portfolios. Therefore, the CAPM beta cannot account for the return spread between growth and value stocks.

I demonstrate that uncertainty shocks can drive the value premium by having a differential impact on cross-sectional firms depending on their holdings of growth options. The main intuition is that the value of growth options increases when uncertainty is high, since high uncertainty expands the upside of future outcomes. As a result, when uncertainty increases, growth stocks, which have more growth options, do better than value stocks. Therefore, growth stocks are hedges against uncertainty risk and have lower risk premiums than value stocks.

I show this in an investment-based asset pricing model augmented with time-varying uncertainty by allowing the variances of both aggregate and firm-specific productivity shocks to change over time. Uncertainty affects firms differentially according to the amount of their growth options. The channel is the interaction between uncertainty, investment opportunities, and adjustment costs. When firms change their level of capital, they face adjustment costs, such as fixed costs and investment irreversibility. These frictions cause investment opportunities to behave like financial call options. Investment corresponds to the exercise of the option, while the firm has the right to wait until prospects improve. This option is valuable since it gives the firm access to upside benefits. The value of options, like financial call options, increases with volatility. Adjustment costs generate the optionality in the model, and time-varying uncertainty causes the value of options to change over time.

The model generates a sizable value premium while replicating the empirical failure of the CAPM in accounting for the value premium. This is an important finding as most prior studies that reproduce the value premium do not capture the CAPM's failure. For example, Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Cooper (2006), Ozdagli (2012), and Obreja (2013) produce the value premium, but their market betas also increase with book-to-market. In these studies, the model-generated value premium can be counterfactually explained by the CAPM. These results are common in models with a single source of aggregate risk by which market returns are mainly driven. Consequently, risk premiums tend to be highly correlated with the model-generated market betas contradicting empirical evidence. To resolve this counterfactual prediction, one needs to include additional sources of aggregate risk. My model reproduces the failure of the CAPM by introducing uncertainty shocks as the second source of aggregate risk. I show that the return spread on book-to-market portfolios are mainly driven by uncertainty shocks, while market returns are mostly driven by productivity shocks. As a result, the model can separate risk premia from market betas and generate both flat betas and significant alphas.

Empirical evidence supports the model's predictions. Using the VIX index as a proxy for uncertainty, I show that the returns of growth stocks have higher exposures to changes in uncertainty than those of value stocks. This evidence implies that growth stocks tend to do better than value stocks when uncertainty is high. In addition, I find no distinct pattern in the sensitivities to productivity shocks across the portfolios, using Utilization-adjusted Total Factor Productivity (TFP) as a proxy.

Uncertainty shocks also have a large impact on corporate investment. Bernanke (1983), Leahy and Whited (1996), Bloom (2009), and Kahle and Stulz (2013) show that higher uncertainty reduces investment. My model provides a quantitative prediction on how uncertainty affects investment in the cross-section of firms. I find that value firms sharply reduce investment when uncertainty rises, while growth firms tend to invest even in the presence of heightened uncertainty. This finding indicates that uncertainty influences investment through Tobin's Q. The positive relation between Tobin's Q and investment offsets the negative impact of uncertainty on investment. Consequently, the investment of firms with high Tobin's Q is not significantly affected by uncertainty, while that of firms with low Tobin's Q is adversely affected by uncertainty.

The organization of the paper is as follows. Section 2 reviews the related literature. Section 3 presents some empirical tests. Section 4 describes the model. Section 5 calibrates the model and presents the quantitative results from simulations. Section 6 concludes.

1.2 Related Literature

This paper is related to a recent series of studies on how uncertainty shocks affect macroeconomic variables, including Bloom, Bond, and Reenen (2007), Bloom (2009), Fernandez-Vilaverde and Rubio-Ramrez (2010), Arellano, Bai, and Kehoe (2012), Baker and Bloom (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Christiano, Motto, and Rostagno (2012), Schaal (2012), and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014). These studies show that uncertainty negatively influences investment, consumption, output, and employment. My paper differs from the existing literature in that it focuses on asset prices. In addition, it investigates whether uncertainty shocks have an differential impact on the cross-section of investment depending on firms' characteristics while prior studies explore the relation between uncertainty and aggregate investment.

My work is also connected to Merton (1973)'s ICAPM. With time-varying investment opportunities, factors in asset-pricing models should include state variables that predict future investment opportunity sets. If an asset has a high covariance with a state variable that improve the investment opportunity set, it has high risk premiums since the asset tends to perform poorly when investment opportunities deteriorate. In an ICAPM setting, Campbell and Vuolteenaho (2004) and Campbell, Polk , and Vuolteenaho (2010) argue that value stocks have higher average returns since growth stocks perform better when the expected return on the stock market declines. Campbell, Giglio, Polk, and Turley (2013) point out that increase in the volatility of stock returns also deteriorates investment opportunities. They allow for stochastic volatility and show that growth stocks do well when the volatility of stock returns increases.

Beside Campbell, Giglio, Polk, and Turley (2013), a series of empirical studies have explored the role of stochastic volatility in explaining asset prices. Bakshi and Kapadia (2003), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), and Carr and Wu (2009) find that shocks to market volatility are negatively priced. Bansal and Yaron (2004) incorporate stochastic consumption volatility into a consumption-based asset pricing framework and show that an increase in volatility lowers asset prices. Several recent studies examine the impact of stochastic volatility on cross-sectional returns. Bansal, Kiku, Shaliastovich, and Yaron (2014) and Segal, Shaliastovich, and Yaron (2014) explains the effects of stochastic volatility on cross-sectional returns in the long-run risk framework. My paper differs from those by constructing a structural model to investigate how different holdings of growth options across firms can account for the patterns in their cross-sectional returns. McQuade (2013) also explains the cross-sectional returns based on a structural model with time-varying volatility. My model quantitatively show the impact of time-varying uncertainty on the cross-section of returns while his explanation is qualitative.

This study is also related to the theoretical literature on the value premium. Carlson, Fisher, and Giammarino (2004) investigate the effect of operating leverage on expected returns and demonstrate that the value effect is related to fixed operating costs. Zhang (2005) shows that value stocks are riskier in the presence of investment irreversibility and counter-cyclical price of risk and have higher average returns than growth stocks. Cooper (2006) incorporates fixed adjustment costs of capital as well as investment irreversibility to explain the value effect. However, these models are based on a single source of aggregate risk, and as a result, they counterfactually generate higher market betas for value firms than for growth firms. In contrast, my model is able to replicate the failure of the CAPM by having two sources of aggregate risk, namely, productivity and uncertainty shocks.

This paper is part of the recent literature that explains both cross-sectional returns and the empirical failure of the CAPM by including additional sources of aggregate risk. Kogan and Papanikolaou (2013) include investment-specific shocks. Ai and Kiku (2013) allow for two sources of aggregate risk, namely, long-run and short-run risk in aggregate consumption growth. Belo, Lin, and Bazdresch (2014) use stochastic adjustment costs, and Belo, Lin, and Yang (2014) use shocks to external financing costs.

1.3 Empirical Findings

In this section, I conduct some empirical analysis to examine the link between uncertainty and cross-sectional returns. First, I test whether uncertainty shocks can explain the spread in returns between value stocks and growth stocks. To this end, I run rolling monthly regressions to obtain the loadings of 10 book-to-market sorted portfolios on the innovations in uncertainty. If the value of growth stocks increases with uncertainty, they should have higher loadings on the innovations in uncertainty. Prior studies show that innovations to aggregate volatility or macroeconomic uncertainty are negatively priced (see, for example, Bakshi and Kapadia (2003), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), Carr and Wu (2009), Campbell, Giglio, Polk, and Turley (2012), Boguth and Kuehn (2013), and Bansal, Kiku, Shaliastovich, and Yaron (2014)). Given this finding, if growth stocks have significantly higher loadings on innovations in uncertainty than value stocks, then this can account for the value premium.

Second, I examine whether productivity shocks influence growth stocks and value stocks differently. The model in this study has two sources of aggregate risk, namely, productivity shocks and uncertainty shocks. Using a proxy for productivity shocks, I examine how productivity shocks affect the cross-section of stock returns. If productivity shocks generate differential effects across the portfolios, the impact of uncertainty shocks may be subsumed by that of productivity shocks, and consequently, the uncertainty shocks may not be the main driving force of the value premium.

1.3.1 Data

I use the VIX index as a proxy for uncertainty. The VIX is the implied volatility of the Standard & Poor's 500 portfolio, calculated from the prices of put and call options traded on the Chicago Board Options Exchange (CBOE). The data are taken from CBOE, and the sample period is from January 1990 to December 2013 due to the data availability. A daily series of the VIX is aggregated to a monthly frequency by averaging the daily values within the month.

As a proxy for productivity shocks, I use Utilization-adjusted Total Factor Productivity (TFP).[1] The data are obtained from the Federal Reserve Bank of San Francisco. Since the data of Utilization-adjusted TFP are quarterly, I aggregate returns on the portfolios and the VIX by averaging their monthly values within the quarter when conducting the regression analysis that involves TFP. When TFP is used as a single factor for regressions, the sample period is from 1963 to 2013. For regressions that include the VIX together with TFP, the sample period is restricted by the VIX data availability, and the sample period narrows to from January 1990 to December 2013.

1.3.2 Uncertainty and Cross-sectional Returns

This study predicts that growth stocks tend to do better than value stocks when uncertainty rises, since the value of growth options increases with uncertainty. To examine this prediction, I run a regression of returns on 10 book-to-market portfolios on the proxy for innovations in uncertainty:

$$r_{it} = \alpha_i + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}, \tag{1.1}$$

[1] I also use Business-sector TFP as a proxy for productivity shocks, and the results are quantitatively similar.

where r_{it} is the excess return of portfolio i at time t, ΔVIX_t is the innovation in the VIX index, and β_i^{VIX} is the loading of portfolio i on uncertainty risk. In addition, I run the following regression:

$$r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}, \tag{1.2}$$

where MKT_t is the market excess return and β_i^{MKT} is the loading of portfolio i on market risk. By adding MKT, I control for the effect of the market factor on cross-sectional returns. Table 1.1 reports the estimates of risk loadings and their t-statistics in the regressions above when the VIX is used as a proxy for uncertainty. Panel A presents the results of regression (1). It indicates that growth firms tend to have higher risk loadings on innovations in the VIX than value firms. The risk loading of the value minus growth portfolio is -0.22 and is statistically significant ($t = -3.03$). The results imply that when uncertainty is high, value stocks would experience a more severe decrease in their market values than growth stocks. Hence, growth stocks provide a better hedge against uncertainty risk than value stocks.

Panel B of Table 1.1 summarizes the results of regression (2). It shows that after controlling for the market factor, growth stocks still tend to have higher risk loadings on innovations in the VIX than value stocks. In addition, the risk loading of the growth portfolio becomes positive. The loading of the value minus growth portfolio is -0.28 and is statistically significant ($t = -2.79$). Panel B also shows that the loadings on the uncertainty factor exhibit distinct patterns while the loadings on the market factor do not present any pattern.

1.3.3 Aggregate Productivity and Cross-sectional Returns

In this subsection, I first examine whether productivity shocks affect the cross-section of returns. Secondly, I test whether the portfolios have any significant dispersion in their risk loadings on uncertainty shocks after controlling for productivity shocks. To this end, I conduct the following regressions:

$$r_{it} = \alpha + \beta_i^{TFP} \Delta TFP_t + \epsilon_{it} \tag{1.3}$$

$$r_{it} = \alpha + \beta_i^{TFP} \Delta TFP_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}, \tag{1.4}$$

where ΔTFP_t is innovations in TFP, and β_i^{TFP} is loadings of portfolio i on TFP shocks.

Table 1.2 reports the results from the regressions. Panel A presents the results of regression (3). It shows that the risk loadings on productivity shocks do not exhibit significant dispersion. The loading of the value minus growth portfolio is not statistically significant ($t = 1.05$). Panel B reports the result of regression (4). It indicates that growth stocks tend to have higher loadings on the uncertainty factor after controlling for the productivity factor, and that the loading of the value minus growth portfolio is -0.38 and is statistically significant ($t = -2.59$).

I also run regressions controlling for the market factor as follows:

$$r_{it} = \alpha + \beta_i^{MKT} \Delta MKT_t + \beta_i^{TFP} \Delta TFP_t + \epsilon_{it} \tag{1.5}$$

$$r_{it} = \alpha + \beta_i^{MKT} \Delta MKT_t + \beta_i^{TFP} \Delta TFP_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it} \tag{1.6}$$

Table 1.3 presents the results. Both Panel A and Panel B show that loadings on productivity shocks do not have any patterns, and the loading of the value-minus-growth portfolio is not significant. In contrast, loadings on uncertainty shocks tend to decrease with book-to-market, and the loading of the value-minus-growth portfolio is -0.54 and significant at 10% ($t = -1.84$).

In sum, the evidence from empirical tests supports the introduction of uncertainty shocks into the model to explain the cross-section of returns. In Section 4, I examine whether predictions from the model are consistent with empirical findings.

1.4 The Model

In this section, I develop a dynamic investment model of heterogeneous firms to investigate the link between uncertainty shocks and cross-sectional returns. Time-varying uncertainty is introduced into the model by allowing the second moment of both aggregate and firm-specific productivity shocks to vary over time. The model is in a partial-equilibrium setting in which the stochastic discount factor (SDF) is exogenously given.

Firms choose their optimal investment activities in order to maximize their market values. Any change in their current capital stock requires firms to pay adjustment costs of capital. The costs are composed of convex and non-convex components. The non-convex piece reflects that reducing or expanding capital incurs lump-sum costs regardless of how much the capital amount actually changes. It also reflects that disinvestment is more costly than investment. The interaction between uncertainty and non-convex adjustment costs generates regions of inaction where firms prefer to "wait and see" rather than immediately invest or disinvest. Greater uncertainty expands the region of inaction, generating a negative relationship between uncertainty and investment. Therefore, uncertainty influences firms' choices on their optimal investment through non-convex adjustment costs, and consequently, their expected returns.

1.4.1 Production and Investment

In the economy, there is a continuum of firms with heterogeneity in their firm-specific productivity and capital stock. Each firm uses capital to produce a single homogenous good. The production function of firms is given by:

$$Y_{it} = X_t Z_{it} K_{it}^{\eta}. \tag{1.7}$$

At time t, a firm indexed by i produces output Y_{it}, using physical capital K_{it}. The productivity of a firm is composed of aggregate productivity, X_t, and firm-specific productivity, Z_{it}. The aggregate productivity is common to all firms and is a source of aggregate risk. The firm-specific productivity generates heterogeneity across firms. There is also heterogeneity in capital stock. Firms with high productivity relative to their capital are growth firms and have more growth options, while firms with low productivity relative to their capital are value firms and have less growth options. The capital share, $0 < \eta < 1$, implies that the production function exhibits decreasing returns to scale with capital.

Firms accumulate capital through investment. The investment of firms is as follows:

$$I_{it} = K_{it+1} - (1 - \delta) K_{it}, \qquad 0 < \delta < 1 \tag{1.8}$$

where I_{it} denotes firm investment and δ represents the rate of capital depreciation.

1.4.2 Time-varying Uncertainty

I assume that both $x_t \equiv \log X_t$ and $z_{it} \equiv \log Z_{it}$ follow a first-order autoregressive process:

$$x_{t+1} = \bar{x}(1-\rho_x) + \rho_x x_t + \sigma_t^x \varepsilon_{t+1}^x, \tag{1.9}$$

$$z_{it+1} = \rho_z z_{it} + \sigma_t^z \varepsilon_{it+1}^z, \tag{1.10}$$

in which ε_{t+1}^x and ε_{it+1}^z are uncorrelated for all i; ε_{it+1}^z and ε_{jt+1}^z are uncorrelated for any pair of i, j with $i \neq j$; $\bar{x}$ is the long-term mean of aggregate productivity; ρ_x and ρ_z are the persistence of aggregate and firm-level productivity, respectively.

Following Bloom (2009), I define uncertainty as the volatility of innovations to aggregate productivity, σ_t^x, and the volatility of innovations to firm-specific productivity, σ_t^z. They vary over time, following a two-state Markov chain:

$$\sigma_t^x \in \{\sigma_L^x, \sigma_H^x\}, \tag{1.11}$$

$$\sigma_t^z \in \{\sigma_L^z, \sigma_H^z\}, \tag{1.12}$$

$$Pr(\sigma_{t+1} = \sigma_j \quad | \quad \sigma_t = \sigma_k) = \pi_{k,j} \tag{1.13}$$

Time-varying volatility of aggregate productivity generates periods of low and high uncertainty in the economy, while time-varying volatility of firm-specific productivity produces periods of low and high cross-sectional dispersion across firms. Since they both are based on the same Markov process, periods of high economic uncertainty are accompanied by periods of high cross-sectional dispersion, and vice-versa.

1.4.3 Adjustment Costs

Each firm faces adjustment costs of capital whenever they change their current level of capital. Adjustment costs are critical in generating the options value of investment opportunities in the existence of uncertainty. In addition, without the investment frictions, models produce a counterfactually smooth Tobins Q (Boldrin, Christiano, and Fisher (2001)). Adjustment costs include installation costs of new equipment, costs from temporarily shutting down factories for installation, and costs incurred from educating employees on the use of new technology. There are two components in the adjustment costs, namely, convex and nonconvex adjustment costs. Convex adjustment costs were the bedrock of investment models in the 1980s; however, they cannot account for lumpy and intermittent investment patterns at a micro-level. Nonconvex adjustment costs can capture these patterns. Cooper and Haltiwanger (2006) show that the combination of convex and nonconvex adjustment costs fits the micro-level investment data best. The formulations of convex and nonconvex adjustment costs are as follows:

Convex : Convex costs reflect the rate of adjustment of capital stock. That is, more rapid changes are more costly. This feature leads firms to smooth investment expenditures over time. The formulation of convex adjustment costs is $\frac{c}{2}\left(\frac{I_{it}}{K_{it}}-\delta\right)^2 K_{it}$.

Nonconvex : First, firms need to pay fixed adjustment costs when they change their current levels of capital. In the presence of these costs, investment tends to be lumpy since firms aim to avoid incurring the fixed costs frequently. The fixed costs do not depend on the level of investment activity. Instead, they are proportional to their capital stock, meaning the costs are scaled by firm size. This aspect of adjustment costs discourages big firms from growing quickly. Second, investment is partially irreversible. That is, reducing capital is more costly than expanding capital since there are resale losses due to transactions costs, information asymmetry, and the physical costs of resale. This feature reflects the fact that disinvestment occurs with much less frequency than investment. For both types of adjustment costs, firms have an investment threshold and invest only when profitability reaches an upper threshold. The formulation of the nonconvex part incorporates both fixed adjustment costs and investment irreversibility. Firms face a^+K_{it} when they increase capital stock and a^-K_{it} when they decrease capital stock. The upward and downward speed of capital adjustment are determined by a^+ and a^-, respectively, and $a^- > a^+ > 0$ represents the irreversibility of investment.[2]

The adjustment cost function is given by:

$$\Phi(I_{it}, K_{it}) = \begin{cases} a^+K_{it} + \frac{c}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} & \text{for } I_{it} > \delta K_{it} \\ 0 & \text{for } I_{it} = \delta K_{it} \\ a^-K_{it} + \frac{c}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} & \text{for } I_{it} < \delta K_{it}. \end{cases} \tag{1.14}$$

Adjustment costs arise only from net investment, and replacing depreciated capital does not incur any costs. This formulation leads firms to pay the adjustment costs only when they deviate from the non-stochastic steady state of investment rate, δ.

In the presence of adjustment costs, firms are less flexible in adjusting their capital stock. In particular, nonconvex adjustment costs generate the real options for investing when there is uncertainty in the economy. Without nonconvex adjustment costs, the model cannot generate any option value associated with investment opportunities. Firms invest only when their investment is far from the optimal level and the benefit of adjusting capital is beyond the investment threshold. These options of investing

[2]Zhang (2005) shows that asymmetric adjustment costs are important in generating the value premium. Cooper (2006) finds that the irreversibility is the driving force in generating the value effect.

can be interpreted as financial call options. Firms increase the level of installed capital by exercising the options. The value of the options is time-varying since uncertainty varies over time in the model. It increases when uncertainty increases because higher uncertainty generates the higher upside of future growth.

1.4.4 Stochastic Discount Factor

The stochastic discount factor (SDF) is specified as:

$$\log M_{t+1} = \log \beta - \gamma_x (x_{t+1} - x_t) - \gamma_{\sigma^x} (\sigma^x_{t+1} - \sigma^x_t), \tag{1.15}$$

where the subjective discount factor is $\beta > 0$, the price of risk for productivity shocks is $\gamma_x > 0$, and the price of risk for uncertainty shocks, $\gamma_{\sigma^x} < 0$.

The SDF is specified as a function of productivity shocks and uncertainty shocks. The price of each shock reflects its opposite impact on asset prices.[3] The positive sign for γ_x represents the positive market price for productivity shocks, while the negative sign for γ_{σ^x} represents the negative market price for uncertainty shocks. Their opposite signs reflect that productivity risk carries positive premiums while uncertainty risk carries negative premiums. If stocks do well during times of high aggregate productivity and do poorly during times of low aggregate productivity, they earn high average returns. The reason is that these stocks do poorly when the economy is in a bad state. On the other hand, if stocks do well during times of high uncertainty and do poorly during times of low uncertainty, they earn low average returns since they provide insurance against uncertainty risk. An increase in uncertainty is considered

[3]In my model, the prices of risk are constant, which differs from the SDF in Zhang (2005) and Lin and Zhang (2013). Time-varying price of risk is a key ingredient in their models to generate the value premium. In my model, I produce a sizable value premium with constant prices of risk.

as undesirable by investors so that they require compensation for holding stocks with smaller exposure to uncertainty risk. The negative price of volatility risk is supported by prior studies such as Bakshi and Kapadia (2003), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), Carr and Wu (2009), Campbell, Giglio, Polk, and Turley(2012), Boguth and Kuehn (2013), and Bansal, Kiku, Shaliastovich, and Yaron (2014).

1.4.5 Optimal Investment

The profit function for a firm is given by:

$$\Pi_{it} = Y_{it} - f, \tag{1.16}$$

where Y_{it} is output and f is the fixed cost of production, which must be paid by all firms participating in operational activities. The fixed costs generate operating leverage. This operating leverage implies that firms are relatively risky when they operates at low values of productivity because the costs are common for all firms with different levels of productivity. It also implies that firms with low levels of capital are relatively risky since the costs are common for all firms and do not depend on the capital levels.

I denote by $V(K_{it}, Z_{it}; X_t, \sigma_t^x, \sigma_t^z)$ the value function of a firm. There are five state variables: (1) capital stock, K_{it}; (2) firm-specific productivity, Z_{it}; (3) aggregate productivity, X_t; (4) time-varying aggregate uncertainty, σ_t^x; and (5) time-varying cross-sectional uncertainty, σ_t^z.

Firms choose their investment activities to maximize the present value of their future cash flows, discounted by the exogenously given stochastic discount factor.

Optimal investment is defined as the solution to a dynamic optimization problem defined by the stochastic Bellman equation:

$$
\begin{aligned}
V(K_{it}, Z_{it}; X_t, \sigma_t^x, \sigma_t^z) &= \max_{I_{it}} \{\Pi_{it} - I_{it} - \Phi(I_{it}, K_{it}) \\
&+ E_t[M_{t+1} V(K_{it+1}, Z_{it+1}; X_{t+1}, \sigma_{t+1}^x, \sigma_{t+1}^z)]\} \quad (1.17) \\
s.t. \quad & K_{it+1} = I_{it} + (1-\delta) K_{it}, \quad (1.18)
\end{aligned}
$$

where $V(\cdot)$ is the value function, Π_{it} is a profit function, I_{it} is investment, $\Phi(\cdot)$ is an adjustment cost function, E_t is the expectations operator, and M_{t+1} is the stochastic discount factor. The first three terms on the right hand side of (15) represent the present dividend, which is the firm's profits minus investment minus adjustment costs of capital.

1.5 Quantitative Results

This section presents the quantitative results from the model. In Section 5.1, I discuss the calibration and evaluate whether the model can quantitatively capture the important features in the data. In Section 5.2, the main results from model simulations are presented. In Section 5.3, I investigate the main driving source of the value premium. In Section 5.4, I compute a model-implied the VIX and compare the results with those obtained by using the real VIX index. In Section 5.6, I conduct comparative statics and explore the mechanism in the model. Lastly, in Section 5.5, I investigate the link between uncertainty and cross-sectional investment.

1.5.1 Calibration

Table 1.4 reports parameter values used to calibrate the model. I calibrate the model at a monthly frequency. In total, 100 artificial samples are simulated; each sample has 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulations and to match the length of the sample period with that in the empirical data. I calibrate the model based on two approaches. I first use the parameter values reported in prior literature. I also choose values for parameters to match the selected moments in the data that are presented in Table 1.5. I mainly target annual statistics of risk-free rates, market returns, firm-level investment rates, and firm-level market-to-book ratios. I aggregate the simulated data to yearly in order to compare the target moments from model simulations with annual firm-level accounting data. The sample period for target moments is 1963 through 2013. This period is chosen because the value premium puzzle has been more pronounced since 1963. The firm-level data are taken from COMPUSTAT. The returns of book-to-market sorted portfolios, risk-free rates, and market returns are taken from Kenneth French's website.

Productivity: The capital share, η, is chosen to be 0.6, which is close to the value estimated by Cooper and Ejarque (2001) and Hennessy and Whited (2007). The persistence of aggregate productivity, ρ_x, is set to be 0.983, following Cooley and Prescott (1995). They report that the quarterly autocorrelation for the aggregate output is 0.95. Since I calibrate the model at a monthly frequency, I set $\rho_x = 0.95^{\frac{1}{3}} = 0.983$. I set the persistence of the firm-specific productivity, $\rho_z = 0.97$, following Zhang (2005). The long-term average of aggregate productivity is set to be -3.954

to normalize the average long-term capital stock at unity. For fixed operating costs, I set $f = 0.003$ to match the median of the firm-level market-to-book-ratio of 1.64.

Uncertainty process: I set the average volatility of the aggregate productivity, following Cooley and Prescott (1995). They document the quarterly volatility for the aggregate output to be 0.007. I convert it into the monthly value, $\sigma^x = 0.007 \times \sqrt{1 + \rho_x^2 + \rho_x^4} = 0.0041$.[4] There are two states of aggregate productivity volatility, the high and low states, given as σ_L^x and σ_H^x, respectively. Following Bloom (2009), high volatility has twice the value of low volatility, so that σ_L^x and σ_H^x are chosen to be 0.003 and 0.006 to match the average volatility of 0.0041. The average volatility of the firm-specific productivity, ρ_z, is set to be 0.15, following Gomes and Schmid (2010). There are also two states of volatility of firm-specific productivity. These are the high and low states, given as σ_L^z and σ_H^z, respectively. High volatility has twice the value of low volatility, so that σ_L^z and σ_H^z are set to be 0.108 and 0.217 to match their average value of 0.15. The transition probabilities for the uncertainty process, namely $\pi_{L,L}$ and $\pi_{H,H}$, are from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). They calibrate the quarterly transition probabilities as 0.95 and 0.92. I convert the values into monthly values and set $\pi_{L,L} = 0.983$ and $\pi_{H,H} = 0.972$.

Adjustment costs: The monthly rate of depreciation, δ, is set to be 0.01, close to the empirical estimate of Cooper and Haltiwanger (2000). The parameter for convex adjustment costs, c, is chosen to be 0.05 to match the annual volatility of the firm-level investment rates of 22.30%. The parameter for nonconvex adjustment costs, a^+ and a^-, are chosen to be 0.01 and 0.08 respectively, so that the model can match the

[4]The formulas that I use to convert the quarterly values to monthly values are from Heer and Maussner (2009).

median of the firm-level investment rates, 11.58%, and the range of the average ratio of adjustment costs-to-output of $0 - 4.2\%$, as estimated in Hall (2004) and Merz and Yashiv (2007).

Stochastic discount factor: The subjective discount factor, β, is chosen to be 0.985 to match the average annual risk-free rates of 1.03%. I set the price of risk for productivity shocks to be $\gamma_x = 8$ and price of risk for uncertainty shocks to be $\gamma_{\sigma^x} = -15$ to match the mean and volatility of market returns, which are 7.01% and 17.35% respectively, as well as the volatility of the risk-free rate of 2.31%.

The comparison between target moments from data and those from model simulations is summarized in Table 1.5. It shows that averages and volatilities for risk-free rates and market returns from the model and the real data are closely matched. The average of market returns from the model is higher than that from the data. The statistics for firm-level investment rates, market-to-book ratios, and average adjustment costs-to-output ratio are reasonably matched.

1.5.2 The value premium

In this subsection, I compare the value premium in the data with that which was generated from model simulations. Table 1.6 reports descriptive statistics of 10 book-to-market portfolios, including the mean excess returns ($E(r)$), return volatility ($\sigma(r)$), abnormal returns (α), and market betas (β) from the CAPM regressions. Panel A in Table 1.6 represents the statistics in the data. It shows that the value premium is 7.35% per year. The CAPM alpha of the value-minus-growth decile is 7.13% and statistically significant (t-value = 2.26), while its market beta is not statistically different from zero. These results indicate that there is no association between market betas and the return spread across book-to-market portfolios. The market betas cannot generate enough dispersion to explain the return spread across the portfolios. One of the goals of this study is to replicate Panel A by generating both the value premium and the failure of the CAPM to account for the value premium.

Panel B in Table 1.6 summarizes the simulation results from the model. The book value of the firm is defined as its capital stock, and the market value of the firm is defined as its *ex* dividend stock price.[5] I follow Fama and French (1992, 1993) to form 10 book-to-market portfolios for each simulated panel. I repeat the entire simulation 100 times and report the cross-simulation averages of the summary statistics in the table. Panel B shows that the value premium generated from the model is 4.37%. In addition, the model replicates the failure of the CAPM. The CAPM betas are flat across book-to-market portfolios, and thus, they cannot capture the dispersion between the growth and the value portfolios. The beta of the value-minus-growth decile is not statistically different from zero, and its alpha is 4.20% and statistically significant (t-value = 4.16). Therefore, the CAPM cannot account for the value premium, which is consistent with the empirical evidence.

Reproducing the failure of the CAPM in the model is a key contribution of this paper. The models in prior studies on the value effect generate high betas for value stocks and low betas for growth stocks. As a result, the return difference between growth and value stocks can be counterfactually explained by the CAPM. (see Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005),

[5] $V(K_{it}, Z_{it}; X_t, \sigma_t^x, \sigma_t^z)$ is the *cum* dividend stock price. The current dividend is defined as $D_{it} = \Pi_{it} - I_{it} - \Phi(I_{it}, K_{it})$. The *ex* dividend stock price is the firm value after dividend is paid out.

Ozdagli (2012), and Obreja (2013)). This issue is common in models with one source of aggregate risk. In the economy with one aggregate shock, the CAPM betas are highly correlated with risk premiums. This paper shows that by adding time-varying uncertainty risk as a second source of risk, the model generates a multifactor structure of returns and breaks the high correlation between market betas and risk premiums in the prior models.

1.5.3 The Risk Source of the Value Premium

This subsection explores what drives the cross-section of returns in the model. To this end, I examine the loadings on two risk factors in the model, namely, productivity shocks and uncertainty shocks. Section 3 shows that in the data, book-to-market portfolios have differential exposures to the uncertainty factor, while they have almost the same exposures to the productivity factor and the market factor. This evidence provides support for the explanatory power of uncertainty shocks on the value premium. I test whether the model generates results consistent with those in the data.

In the model, uncertainty shocks are defined as the first difference between the current and lagged volatility of innovations to aggregate productivity. Table 1.7 reports the regression results of 10 book-to-market portfolios on uncertainty shocks. Panel A indicates that the loadings on uncertainty risk have a sizable spread and decrease from the growth to value portfolios. The loading of the value minus growth portfolio is -3.13 and is statistically significant ($t = -1.83$) at 10%. Panel B reports the loadings on uncertainty risk controlling for the market factor. It shows that the loadings on uncertainty shocks monotonically decrease from the growth to value portfolios, while there are no significant patterns in the loadings on market risk. The loadings of growth stocks on uncertainty shocks become positive after adding the market factor to the regression model. The loading of the value minus growth portfolio is -3.04 and is statistically significant ($t = -1.82$) at the 10%. The results show that growth stocks tend to do better than value stocks when uncertainty increases. These results are consistent with those from the data reported in Section 3.2.

I investigate whether productivity shocks have a differential impact on cross-sectional returns. If this is the case, the value premium generated from the model might be explained by productivity shocks rather than uncertainty shocks. Table 1.8 summarizes the test results. Panel A shows that the portfolios do not exhibit a sizable spread in their sensitivities to productivity shocks. Panel B shows that the portfolios still have different sensitivities after controlling for productivity shocks. The loading of the value-minus-growth portfolio is -3.02 and is statistically significant ($t = 1.76$) at 10%. I also run regressions including the market factor, and present the results in Table 1.9. It shows that the risk loadings on productivity shocks do not exhibit any patterns, while loadings on uncertainty shocks decrease with book-to-market. These results are consistent with the empirical findings presented in Section 3.3. Therefore, in the model, uncertainty shocks are the driving force behind the value premium.

1.5.4 Model-implied VIX Index

I compute a model-implied VIX index to make the results from the model comparable with those from the data. This index is defined as the expected conditional volatility of market returns. The model-implied VIX is calculated as follows:

$$VIX_t = 100 \times \sqrt{12 \times VAR_t(R^M_{t+1})}, \tag{1.19}$$

where $VAR_t(R^M_{t+1})$ is the monthly conditional variance of market returns. I convert the monthly conditional variance into annualized volatility in percentages, following the construction of the real VIX index.

I conduct the same analysis as that in the previous subsection, using the model-implied VIX, and then compare the results with those from the data. Table 1.10 reports these results. It shows that the results are consistent with those using the real VIX index, which were presented in Sections 3.2 and 3.3. The loadings on the model-implied VIX decrease from growth to value stocks. The pattern remains after controlling for the market factor or the productivity factor. In addition, Panel B indicates that the loadings of growth stocks change from negative to positive after adding the market factor to the regression model. The results show that the model captures the link between the cross-section of returns and the VIX index that proxies for uncertainty.

1.5.5 Comparative Statics

In this subsection, I conduct alternative calibrations with different values for the model parameters in order to investigate the mechanism by which the model generates the value premium. These experiments shed light on understanding which channels make significant contributions to generating the differential effects of uncertainty shocks on cross-sectional returns. The comparison results are reported in Table 1.11. The first column shows the results from the benchmark model. The model generates a value premium of 4.37%, and the CAPM alpha of the value-minus portfolio is 4.20%.

First, I shut down uncertainty shocks in specification 1 by setting constant volatilities for both aggregate and firm-specific productivity shocks (i.e., $\sigma_x^L = \sigma_x^H = 0.0041$

and $\sigma_z^L = \sigma_z^H = 0.15$). Without the time-varying uncertainty, the model generates a value premium of 2.85%. In specification 2, I shut down firm-specific uncertainty shocks by setting $\sigma_z^L = \sigma_z^H = 0.15$. When there are only aggregate uncertainty shocks, the value portfolio earns annual average returns that are 2.28% higher than those of the growth portfolio. The value premium is small compared with that from the benchmark model, which implies that firm-specific uncertainty shocks are also important in producing the value premium. It seems that firm-specific uncertainty shocks amplify the impact of the time-varying aggregate uncertainty shocks. In specification 3, I assume that there is no price of risk for uncertainty shocks by setting $\gamma_{\sigma^x} = 0$. With the setting, the model produces 2.71% of the value premium.

Specifications 4, 5, and 6 show the role of each component for adjustment costs. In specification 4, I shut down the convex part of the adjustment costs by setting the coefficient of the convex term, c, to zero. Without the convex component, the model generates 3.21% of the return spread between the growth and the value portfolios. The model can still produce the value premium, but the magnitude is smaller than that of the model with the convex term in adjustment costs.

In specification 5, I remove investment irreversibility by setting the coefficient of nonconvex adjustment costs of disinvestment, a^-, to be equal to that of investment, a^+ . This means that disinvestment is no longer more expensive in the model. After removing the irreversibility, the model generates 1.02% of the value premium. This result implies that irreversibility of investment is critical in generating the value premium. This finding is consistent with Zhang (2005) and Cooper (2006).

Lastly, in specification 6, I get rid of the nonconvex adjustment costs by setting the coefficients of the costs, namely a^+ and a^-, to zero. By doing so, firms only need to pay convex adjustment costs to change their current level of capital. The result shows that there is no value premium without the nonconvex adjustment costs. Therefore, the nonconvex adjustment costs play a key role in producing the value premium. This implies that without nonconvex adjustment costs, there is no optionality in the model, and as a result, investment opportunities are not like financial call options. The value of investment opportunities no longer interact with uncertainty.

1.5.6 Uncertainty and Cross-sectional Investment

A series of empirical and theoretical studies shows that uncertainty has a significantly negative impact on corporate investment.[6] However, the impact of uncertainty on cross-sectional investment is less emphasized. In this subsection, I explore whether corporate investment exhibits heterogeneous reactions to uncertainty depending on the amount of each firm's investment opportunities.

Table 1.12 compares annual average investment rates across book-to-market portfolios during low uncertainty and high uncertainty. It shows that the investment rate of extreme growth firms increases by 3.82% while investment rates of other firms drop. In addition, the table indicates that firms with higher book-to-market ratios exhibits a greater magnitude of reduction in their investment rates. This finding implies that the impact of uncertainty on investment is negatively related to book-to-market ratios.

To assess the effect of uncertainty on cross-sectional investment, I run the following regression using the model-generated data:

$$\frac{I_{it}}{K_{it}} = a_i + \lambda_i \sigma_t + \epsilon_{it}, \tag{1.20}$$

[6] See, for example, Bernanke (1983), Leahy and Whited (1996), Guiso and Parigi(1999), Bloom, Bond, and Reenen (2007), Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Stein and Stone (2012), Kahle and Stulz (2013), and Gilchrist, Sim and Zakrajsek (2014).

where I_{it} is an investment flow of portfolio i over time t and K_{it} is capital stock at the beginning of time t. σ_t is uncertainty at time t, defined as the volatility of innovations to aggregate productivity.[7] I also run the same regression using the model-implied VIX index.

Table 1.13 reports estimates of the impact of uncertainty on the investment of 10 book-to-market portfolios. Panel A shows that uncertainty positively affects the investment of firms with lowest book-to-market rations while it has a significantly negative impact on investment of other firms. Panel B indicates that the results using the model-implied VIX are consistent with those in Panel A. The finding in Table 1.13 suggests that uncertainty has an impact on cross-sectional investment. Investment of firms with high Tobin's Q is positively affected by uncertainty while that of firms with low Tobin's Q is negatively affected. This implies that uncertainty affects investment through Tobin's Q, which is consistent with Dixit and Pindyck (1994) and Abel and Eberly (1983). They show that in the presence of investment irreversibility, uncertainty has an effect on investment only through marginal Q. Since the production function in the model exhibits decreasing returns to scale, Tobin's Q is not equal to marginal Q. However, it can serve as a proxy for marginal Q.

The results imply that the positive relation between Tobin's Q and investment tends to cancel out the negative effect of uncertainty on investment. As a result, firms with high Tobin's Q are not affected by uncertainty and proceed with their investment, while firms with low Tobin's Q significantly decrease their investment during times of high uncertainty.

[7]Capital stock, K_{it},and uncertainty level, σ_t are known at the beginning of time t. Firms determine their optimal investment, I_{it}, based on K_{it} and σ_t.

1.6 Conclusion

This study examines the effect of uncertainty shocks on the cross-section of stock returns. Uncertainty has a heterogeneous impact across book-to-market portfolios. Growth firms tend to do better than value firms when uncertainty rises, and therefore, provide a better hedge against uncertainty shocks. The reason for this is that the value of growth options increases with uncertainty.

By introducing uncertainty shocks into an investment-based asset pricing model, my model can reproduce both the value premium and the empirical failure of the CAPM. As such, the model with uncertainty shocks generates a multifactor structure in stock returns and reduces the high correlation between CAPM betas and risk premiums in the models of prior studies on the value premium. The nonconvex adjustment costs of investment play a critical role in producing the value premium. The combination of irreversibility and fixed costs of investment generates the optionality in the model. The value of options is time-varying since uncertainty varies over time. The results from comparative statics show that the model cannot generate the value premium without the nonconvex adjustment costs.

This study also finds that uncertainty affects the cross-section of investment. The investment of value firms is negatively affected by uncertainty, while that of growth firms is positively affected. This finding suggests that uncertainty influences corporate investment through Tobin's Q. Firms with higher Tobin's Q have greater ability to proceed with their investment regardless of uncertainty.

1.7 Tables and Figures

Figure 1.1: **Average Returns of Book-to-Market Portfolios and the CAPM**

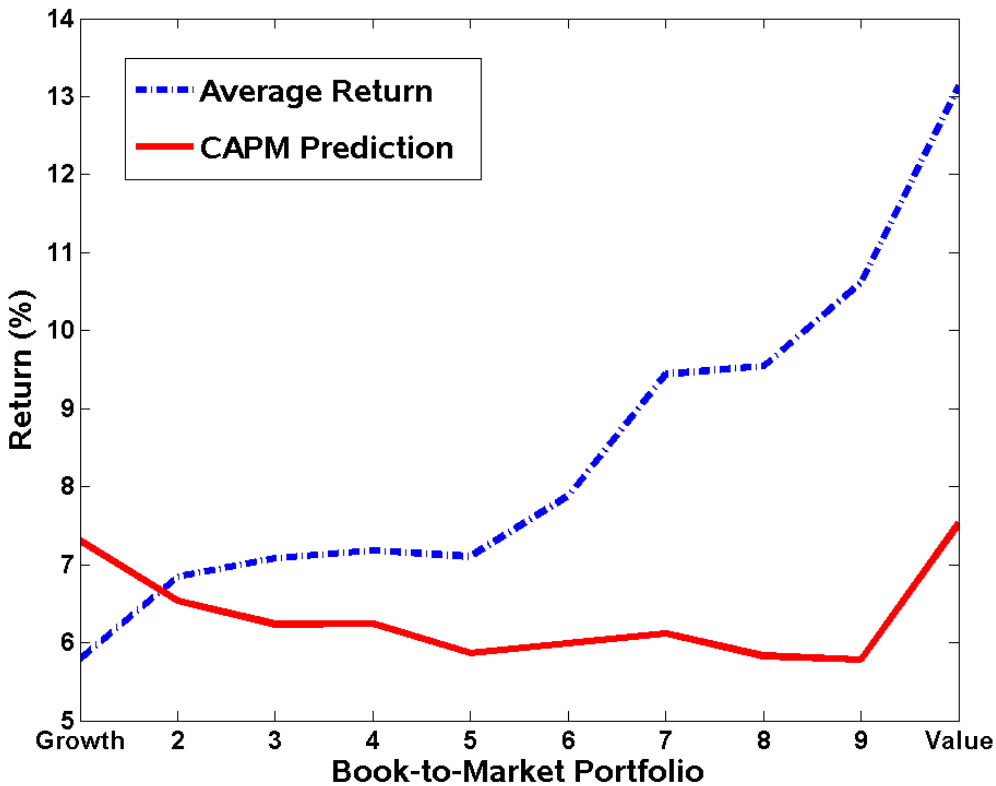


Table 1.1: **VIX and Cross-sectional Returns**

This table reports the estimated loadings on risk factors of 10 book-to-market portfolios and their t-statistics from the following two regressions:

Panel A: $r_{it} = \alpha_i + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$

Panel B: $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t, ΔVIX is the innovation in the VIX index, MKT is the market excess return, and β^{VIX} and β^{MKT} are loadings on uncertainty risk and market risk, respectively. The VIX index is obtained from CBOE (Chicago Board Options Exchange) and aggregated to a monthly frequency by averaging its daily values within the month. The monthly returns on book-to-market deciles, the risk-free rate, and market portfolio returns are taken from Kenneth French's website. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation. Due to the data availability of the VIX, the sample period is January 1990 through December 2013.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{VIX}	-0.66	-0.68	-0.60	-0.69	-0.67	-0.70	-0.61	-0.65	-0.69	-0.88	-0.22
$t_{\beta^{VIX}}$	-10.65	-11.56	-6.84	-10.24	-8.30	-10.88	-8.76	-10.39	-9.20	-11.00	-3.03
					Panel B						
β^{MKT}	1.08	0.94	0.92	0.91	0.82	0.90	0.82	0.81	0.89	1.00	-0.08
$t_{\beta^{MKT}}$	21.69	23.94	24.62	13.57	12.84	13.78	11.58	6.90	10.50	8.47	-0.47
β^{VIX}	0.07	-0.04	0.02	-0.07	-0.11	-0.08	-0.05	-0.11	-0.09	-0.21	-0.28
$t_{\beta^{VIX}}$	1.63	-1.11	0.48	-1.55	-1.88	-1.88	-1.10	-1.31	-1.53	-2.93	-2.79

Table 1.2: **TFP and Cross-sectional Returns**

This table reports the estimated loadings on risk factors of 10 book-to-market portfolios and their t-statistics from the following two regressions:

Panel A: $r_{it} = \alpha_i + \beta_i^{TFP} \Delta TFP_t + \epsilon_{it}$

Panel B: $r_{it} = \alpha_i + \beta_i^{TFP} \Delta TFP_t + \beta_i^{VIX} \Delta U_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t, ΔTFP is the innovation in Utilization-adjusted total factor productivity, ΔVIX is the innovation in the VIX index, and β^{TFP} and β^{VIX} are loadings on productivity risk and uncertainty risk, respectively. The returns of book-to-market deciles, the risk-free rate, and market portfolio returns are taken from Kenneth French's website. Since TFP data are quarterly, the portfolio returns and the VIX are averaged over every three months to form quarterly observations. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation. The sample period is January 1963 to December 2013 for Panel A and January 1990 to December 2013 for Panel B, due to limited data availability of the VIX.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{TFP}	0.22	0.13	-0.02	-0.05	0.05	0.02	0.12	0.19	0.20	0.43	0.21
$t_{\beta^{TFP}}$	0.73	0.56	-0.08	-0.21	0.23	0.10	0.56	0.81	0.94	1.68	1.05
					Panel B						
β^{TFP}	0.37	0.22	-0.04	-0.16	0.02	-0.14	-0.06	-0.00	0.04	0.33	-0.04
$t_{\beta^{TFP}}$	1.41	0.98	-0.20	-0.64	0.08	-0.73	-0.24	-0.01	0.15	1.06	-0.09
β^{VIX}	-0.92	-0.89	-0.75	-0.96	-0.85	-1.01	-0.86	-1.02	-0.95	-1.30	-0.38
$t_{\beta^{VIX}}$	-6.24	-4.78	-3.02	-5.00	-3.85	-5.87	-4.02	-7.58	-4.15	-5.49	-2.55

Table 1.3: **TFP and Cross-sectional Returns, Controlling for Market Risk**

This table reports the estimated loadings on risk factors of 10 book-to-market portfolios and their t-statistics from the following regressions:

Panel A: $r_{it} = \alpha + \beta_i^{MKT} MKT_t + \beta_i^{TFP} \Delta TFP_t$

Panel B: $r_{it} = \alpha + \beta_i^{MKT} MKT_t + \beta_i^{TFP} \Delta TFP_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t, MKT is market excess returns, ΔTFP is the innovation in Utilization-adjusted total factor productivity, ΔVIX is the innovation in the VIX index, and β^{TFP}, β^{MKT}, and β^{VIX} are loadings on market factor, productivity risk, and uncertainty risk, respectively. A quarterly series of Utilization-adjusted TFP is obtained from the Federal Reserve Bank of San Francisco, and the VIX is from CBOE. The returns of book-to-market deciles, the risk-free rate, and market portfolio returns are taken from Kenneth French's website. Since TFP data are quarterly, the portfolio returns, market excess returns, and the VIX are averaged over every three months to form quarterly observations. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation. The sample period is January 1963 to December 2013 for Panel A and is January 1990 to December 2013 for Panel B, due to the limited data availability of the VIX.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{MKT}	1.09	1.02	0.99	0.98	0.87	0.91	0.90	0.88	0.95	1.06	-0.03
$t_{\beta^{MKT}}$	1.09	1.02	0.99	0.98	0.87	0.91	0.90	0.88	0.95	1.06	-0.03
β^{TFP}	0.07	0.01	-0.15	-0.18	-0.07	-0.10	0.01	0.09	0.09	0.30	0.23
$t_{\beta^{TFP}}$	0.79	0.14	-2.88	-3.09	-1.05	-1.59	0.17	1.06	0.95	2.24	1.13
					Panel B						
β^{MKT}	1.05	0.95	0.98	0.89	0.78	0.87	0.88	0.75	0.89	0.87	-0.18
$t_{\beta^{MKT}}$	12.30	16.10	16.83	8.67	6.82	9.58	6.68	5.27	6.76	4.45	-0.66
β^{TFP}	0.29	0.14	-0.12	-0.23	-0.05	-0.21	-0.13	-0.06	-0.04	0.26	-0.03
$t_{\beta^{TFP}}$	1.56	1.28	-1.62	-1.77	-0.41	-2.13	-0.84	-0.35	-0.19	0.78	-0.06
β^{VIX}	0.03	-0.03	0.14	-0.15	-0.14	-0.22	-0.05	-0.34	-0.13	-0.51	-0.54
$t_{\beta^{VIX}}$	0.28	-0.52	1.61	-1.53	-0.93	-2.30	-0.37	-2.60	-0.90	-2.70	-1.84

Table 1.4: **Parameters**

This table reports the values for parameters used to calibrate the model. The model is calibrated at a monthly frequency.

Parameter	Notation	Value
Productivity		
Capital share	η	0.6
Persistence of aggregate productivity	ρ^x	0.983
Persistence of idiosyncratic productivity	ρ^z	0.97
Long-term average of aggregate productivity	$\bar{x}$	-3.954
Fixed operating costs	f	0.003
Uncertainty process		
Low volatility of aggregate productivity	σ_L^x	0.003
High volatility of aggregate productivity	σ_H^x	0.006
Low volatility of firm-specific productivity	σ_L^z	0.108
High volatility of firm-specific productivity	σ_H^z	0.217
Probability of staying in the low volatility state	$\pi_{L,L}$	0.983
Probability of staying in the high volatility state	$\pi_{H,H}$	0.972
Adjustment costs		
Depreciation rate	δ	0.01
Convex costs	c	0.05
Nonconvex costs of positive investment	a^+	0.01
Nonconvex costs of negative investment	a^-	0.08
Stochastic discount factor		
Subjective discount factor	β	0.985
Price of risk for productivity shocks	γ_x	8
Price of risk for uncertainty shocks	γ_{σ^x}	-15

Table 1.5: **Target Moments**

This table compares target moments from the data with those from model simulations. 100 samples are simulated, and each includes 1000 month and 5000 firms. The first 400 months are dropped to neutralize the impact of initial conditions and to match the length of the sample period with that in the empirical data. The moments from model simulations are aggregated to an annual level. The sample period of the empirical data is from 1963 to 2013. The firm-level data are taken from COMPUSTAT and the Center for Research in Security Prices (CRSP). The returns of book-to-market sorted portfolios, risk-free rates, and market returns are taken from Kenneth French's website. The range of the average adjustment costs-to-output ratio is from Hall (2004) and Merz and Yashiv (2007).

	Data	Model
Average risk-free rate (%)	1.03	0.8
Volatility of risk-free rate (%)	2.31	2.22
Average market return (%)	7.01	9.21
Volatility of market return (%)	17.35	18.00
Median of firm-level investment rate (%)	11.58	12.00
Volatility of firm-level investment rate (%)	22.30	20.44
Median market-to-book ratio	1.64	1.61
Average adjustment costs-to-output ratio (%)	0-4.2	2.04

Table 1.6: **Value Premium and CAPM Regressions**

This table compares summary statistics for 10 book-to-market portfolios, including the mean excess returns ($E(r)$), return volatility ($\sigma(r)$), abnormal returns (α), and market betas (β) from the empirical data and model simulations. The mean excess returns, return volatility, and abnormal returns are reported in annual percentages. The sample period of the real data is from 1963 to 2013. The returns on book-to-market portfolios, risk-free rates, and market returns are obtained from Kenneth French's website. For the model, 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A: Data						
$E(r)$	5.78	6.84	7.08	7.18	7.11	7.88	9.44	9.54	10.62	13.14	7.35
$\sigma(r)$	21.33	18.07	17.11	18.55	17.55	17.40	18.72	18.52	18.26	24.31	20.64
α	-1.52	0.30	0.85	0.94	1.24	1.89	3.32	3.71	4.84	5.61	7.13
t_α	-1.22	0.45	1.24	0.80	0.89	1.68	2.38	2.39	4.31	3.12	2.51
β	1.08	0.97	0.92	0.93	0.87	0.89	0.91	0.86	0.86	1.12	0.03
t_β	19.17	28.06	22.19	10.15	9.87	12.94	8.66	7.26	8.62	9.61	0.22
					Panel B: Model						
$E(r)$	7.31	7.90	8.39	8.68	9.31	9.93	10.85	10.93	11.43	11.67	4.37
$\sigma(r)$	15.50	15.22	14.94	14.63	14.61	14.63	14.51	14.83	15.56	16.31	7.06
α	-2.40	-1.67	-1.03	-0.56	0.08	0.70	1.71	1.64	1.79	1.81	4.20
t_α	-6.50	-5.09	-3.76	-2.17	0.33	2.75	6.28	4.54	3.45	2.51	4.16
β	1.04	1.02	1.01	0.99	0.99	0.99	0.98	0.99	1.03	1.05	0.02
t_β	53.98	63.89	90.31	123.83	119.21	130.29	89.78	70.39	39.19	23.16	0.29

Table 1.7: **Value Premium and Uncertainty Risk**

This table reports the exposures of 10 book-to-market portfolios to productivity shocks and their t-statistics using model-generated data. The results are from the following regressions:

Panel A: $r_{it} = \alpha + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it}$

Panel B: $r_{it} = \alpha + \beta_i^{MKT} MKT_t + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t and $\Delta\sigma_t$ is uncertainty shocks defined as the changes in the volatility of innovations to the aggregate productivity in the model. MKT is market excess returns, and β^{σ} and β^{MKT} are loadings on the uncertainty factor and the market factor, respectively. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are averaged from the 100 samples. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{σ}	-5.31	-4.90	-5.12	-6.57	-5.84	-5.87	-6.19	-6.22	-7.35	-8.44	-3.13
$t_{\beta^{\sigma}}$	-1.82	-1.67	-1.58	-2.02	-1.77	-1.69	-1.71	-1.60	-1.69	-1.86	-1.83
					Panel B						
β^{MKT}	1.04	1.02	1.01	0.99	0.99	0.99	0.98	0.99	1.03	1.05	0.02
$t_{\beta^{MKT}}$	53.99	64.16	89.96	124.05	119.27	130.79	88.73	70.18	39.18	23.08	0.25
β^{σ}	0.80	1.13	0.82	-0.75	-0.02	-0.05	-0.43	-0.37	-1.28	-2.24	-3.04
$t_{\beta^{\sigma}}$	1.25	1.76	1.74	-1.75	-0.07	-0.11	-0.73	-0.50	-1.35	-1.89	-1.82

Table 1.8: **Value Premium and Productivity Risk**

This table reports the exposures of 10 book-to-market portfolios to productivity shocks and their t-statistics using model-generated data. The results are from the following regressions:

Panel A: $r_{it} = \alpha_i + \beta_i^{TFP} \Delta TFP_t + \epsilon_{it}$

Panel B: $r_{it} = \alpha_i + \beta_i^{TFP} \Delta TFP_t + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it}$

where r_{it} is the excess return of portfolio i at time t, and $\Delta\sigma_t$ is uncertainty shocks defined as the changes in the volatility of innovations to the aggregate productivity in the model. ΔTFP is productivity shocks, defined as the changes in aggregate productivity. β^{TFP} and β^{σ} are loadings on productivity shocks and uncertainty shocks, respectively. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are averaged from the 100 samples. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
						Panel A					
β^{TFP}	0.58	0.52	0.61	0.69	0.68	0.66	0.66	0.63	0.68	0.78	0.20
$t_{\beta^{TFP}}$	0.97	0.94	1.12	1.33	1.31	1.26	1.30	1.23	1.19	1.25	0.89
						Panel B					
β^{TFP}	0.54	0.49	0.58	0.65	0.64	0.62	0.62	0.60	0.64	0.73	0.18
$t_{\beta^{TFP}}$	0.91	0.88	1.06	1.24	1.23	1.18	1.21	1.14	1.10	1.15	0.79
β^{σ}	-5.00	-4.62	-4.78	-6.19	-5.46	-5.50	-5.82	-5.87	-6.98	-8.02	-3.02
$t_{\beta^{\sigma}}$	-1.64	-1.51	-1.41	-1.83	-1.59	-1.53	-1.56	-1.47	-1.56	-1.72	-1.76

Table 1.9: **Value Premium and Productivity Risk, Controlling for Market Risk**

This table reports the estimated loadings on risk factors of 10 book-to-market portfolios and their t-statistics from the following two regressions:

Panel A: $r_{it} = \alpha + \beta_i^{MKT} MKT_t + \beta_i^{TFP} \Delta TFP_t$

Panel B: $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{TFP} \Delta TFP_t + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t, MKT is market excess returns, ΔTFP is productivity shocks, defined as the changes in aggregate productivity. $\Delta\sigma_t$ is uncertainty shocks defined as the changes in the volatility of innovations to the aggregate productivity in the model. β^{MKT}, β^{TFP}, and β^{σ} are loadings on market factor, TFP factor, and uncertainty factor, respectively. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are average from 100 samples. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{MKT}	1.04	1.02	1.01	0.99	0.99	0.99	0.98	0.99	1.03	1.05	0.02
$t_{\beta^{MKT}}$	54.03	64.08	89.97	123.87	118.12	130.79	90.22	70.40	39.31	23.21	0.27
β^{TFP}	-0.08	-0.12	-0.02	0.07	0.05	0.04	0.05	0.01	0.03	0.11	0.19
$t_{\beta^{TFP}}$	-0.85	-1.76	-0.41	1.27	1.02	0.78	0.72	0.10	0.25	0.72	0.87
					Panel B						
β^{MKT}	1.04	1.02	1.01	0.99	0.99	0.99	0.98	0.99	1.03	1.05	0.01
$t_{\beta^{MKT}}$	54.11	64.49	89.79	124.20	118.20	131.23	89.26	70.23	39.33	23.17	0.23
β^{TFP}	-0.07	-0.12	-0.02	0.07	0.05	0.04	0.04	0.01	0.02	0.10	0.17
$t_{\beta^{TFP}}$	-0.79	-1.65	-0.31	1.17	1.01	0.78	0.68	0.08	0.18	0.63	0.78
β^{σ}	0.76	1.06	0.81	-0.72	0.01	-0.03	-0.41	-0.36	-1.27	-2.18	-2.94
$t_{\beta^{\sigma}}$	1.18	1.61	1.72	-1.69	0.01	-0.06	-0.68	-0.49	-1.31	-1.84	-1.75

Table 1.10: **Value Premium and Model-implied VIX**

This table reports the exposures of 10 book-to-market portfolios to the model-implied VIX index and their t-statistics using model-generated data. The results are from the following regressions:

Panel A: $r_{it} = \alpha_i + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$

Panel B: $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$

Panel C: $r_{it} = \alpha_i + \beta_i^{TFP} \Delta TFP_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}$,

where r_{it} is the excess return of portfolio i at time t, ΔVIX is the changes in the model-implied VIX, defined as the expected conditional volatility of market returns. MKT is market excess returns, and ΔTFP is productivity shocks, defined as the changes in aggregate productivity. β^{VIX}, β^{MKT}, and β^{TFP} are loadings on uncertainty factor, proxied by the model-implied VIX, market factor, and productivity factor, respectively. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are averaged from the 100 samples. Newey-West t-statistics are reported.

	Growth	2	3	4	5	6	7	8	9	Value	V-G
					Panel A						
β^{VIX}	-0.12	-0.11	-0.12	-0.15	-0.13	-0.13	-0.14	-0.14	-0.16	-0.18	-0.06
$t_{\beta^{VIX}}$	-2.06	-2.01	-1.96	-2.50	-2.18	-2.05	-2.17	-1.90	-1.95	-2.18	-1.92
					Panel B						
β^{MKT}	1.04	1.02	1.01	0.99	0.99	0.99	0.98	0.99	1.03	1.05	0.01
$t_{\beta^{MKT}}$	54.06	64.39	89.86	124.07	119.06	131.30	88.92	70.06	39.18	23.07	0.24
β^{VIX}	0.02	0.02	0.02	-0.02	-0.00	-0.00	-0.01	-0.01	-0.02	-0.04	-0.06
$t_{\beta^{VIX}}$	1.45	2.00	1.87	-2.29	-0.37	-0.27	-1.27	-0.40	-1.20	-1.90	-1.93
					Panel C						
β^{TFP}	0.39	0.35	0.43	0.46	0.47	0.46	0.44	0.42	0.43	0.49	0.10
$t_{\beta^{TFP}}$	0.63	0.60	0.76	0.84	0.87	0.83	0.81	0.76	0.71	0.73	0.40
β^{VIX}	-0.10	-0.09	-0.10	-0.12	-0.11	-0.11	-0.12	-0.12	-0.14	-0.16	-0.06
$t_{\beta^{VIX}}$	-1.68	-1.60	-1.49	-1.94	-1.66	-1.58	-1.68	-1.48	-1.56	-1.74	-1.72

Table 1.11: **Comparative Statics**

This table compares the value premium and the CAPM alpha of the value-minus-growth portfolio, generated from the model by alternative calibrations. The first column reports results from the benchmark model. In specification 1, I shut down uncertainty shocks, by setting constant volatilities for both aggregate and firm-specific productivity shocks (i.e., $\sigma_x^L = \sigma_x^H = 0.0041$ and $\sigma_z^L = \sigma_z^H = 0.15$). In specification 2, I turn off firm-specific uncertainty shocks by setting $\sigma_z^L = \sigma_z^H = 0.15$. In specification 3, I set the price of uncertainty risk to be zero (i.e. $\gamma_x = 0$). In specification 4, I shut down the convex part of the adjustment costs by setting its coefficient to zero (i.e., $c = 0$). In specification 5, I remove the investment irreversibility by setting the coefficient of the nonconvex adjustment costs of disinvestment to be equal to that of investment (i.e. $a^+ = a^- = 0.01$). In specification 6, I shut down the nonconvex adjustment costs by setting their coefficients to zero (i.e., $a^+ = a^- = 0$).

	Baseline	No σ shocks	No σ_z shocks	$\gamma_{\sigma_x} = 0$	$c = 0$	$a^+ = a^- = 0.01$	$a^+ = a^- = 0$
$E(r)$	4.37	2.85	2.28	2.71	3.21	1.02	-0.30
α	4.20	1.81	3.22	3.17	6.03	2.61	0.13

Table 1.12: **Investment Rates**

This table reports compares annual average investment rate (I/K) of 10 book-to-market portfolios during periods of low and high uncertainty from model simulations. Monthly average investment rates are annualized by multiplying by 12. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are averaged from the 100 samples.

I/K	Growth	2	3	4	5	6	7	8	9	Value
Low Uncertainty	24.07	18.23	15.81	14.58	13.59	12.92	12.44	11.88	11.48	9.49
High Uncertainty	27.89	16.99	14.25	12.03	10.27	8.80	7.28	6.13	2.55	-4.38
Diff (High-Low)	3.82	-1.25	-1.56	-2.55	-3.32	-4.12	-5.16	-5.75	-8.93	-13.87

Table 1.13: **Uncertainty and Cross-sectional Investment**

This table reports the estimated loadings on risk factors of 10 book-to-market portfolios and their t-statistics from the following regressions:

Panel A: $\frac{I_{it}}{K_{it}} = a_i + \lambda_i^{\sigma}\sigma_t + \epsilon_{it}$

Panel B: $\frac{I_{it}}{K_{it}} = a_i + \lambda_i^{VIX} VIX_t + \epsilon_{it}$,

where I_{it} is an investment flow of portfolio i over time t and K_{it} is capital stock at the beginning of time t. σ_t is uncertainty at time t, defined as the volatility of innovations to aggregate productivity. σ_{t-1} is one-month lagged uncertainty defined as the volatility of innovations to the aggregate productivity in the model. VIX_t is the model-implied VIX index, defined as the expected conditional volatility of market returns. 100 samples are simulated, with each sample containing 5000 firms and 1000 periods. The first 400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that in the empirical data. The reported values are averaged from the 100 samples. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	5	6	7	8	9	Value
					Panel A					
λ^{σ}	1.07	-0.35	-0.44	-0.72	-0.94	-1.16	-1.45	-1.62	-2.51	-3.90
$t_{\lambda^{\sigma}}$	1.94	-1.31	-1.69	-3.91	-5.19	-5.91	-6.06	-6.61	-6.70	-4.45
					Panel B					
λ^{VIX}	0.00	-0.01	-0.01	-0.01	-0.02	-0.02	-0.03	-0.03	-0.04	-0.07
$t_{\lambda^{VIX}}$	1.64	-1.79	-2.36	-4.80	-5.54	-6.40	-6.74	-7.75	-7.64	-4.82

Chapter 2: Uncertainty Shocks and the Idiosyncratic Volatility Puzzle

2.1 Introduction

Ang, Hodrick, Xing, and Zhang (2006, 2009) find that idiosyncratic volatility, measured by the standard deviation of the residuals from the Fama-French three factor model, is negatively priced in the cross-section. This finding has attracted much attention since it is inconsistent with traditional asset pricing theories. For example, according to the capital asset pricing model (CAPM), expected returns on assets are explained only by their sensitivities to market returns, and therefore idiosyncratic volatility should not capture the cross-sectional variation in expected returns. Merton (1987) argues that if markets are incomplete and investors cannot hold well-diversified portfolios, investors will demand compensation for holding under-diversified portfolios. Therefore, idiosyncratic volatility should be positively related to the cross-section of expected returns.

Motivated by my previous work, Koh (2014), I demonstrate in this study that aggregate uncertainty risk can account for the negative relation between idiosyncratic volatility and expected returns (the idiosyncratic volatility puzzle). Koh (2014) shows that a model incorporating time-varying aggregate and idiosyncratic uncertainty can explain the value premium.[8] The study's main intuition is that the value of growth options increases with uncertainty, and therefore stocks with more growth options (growth stocks) hedge uncertainty risk and carry lower risk premiums. It also finds that without time-varying idiosyncratic uncertainty, the magnitude of the value premium from the model decreases by 50%, compared with that from the model with both time-varying aggregate and idiosyncratic uncertainty.[9] This finding suggests that idiosyncratic uncertainty would amplify the positive impact of aggregate uncertainty risk on cross-sectional returns. Everything else being equal, growth stocks with higher idiosyncratic volatilities would have lower expected returns than growth stocks with lower idiosyncratic volatilities since the positive influence of aggregate uncertainty risk on the value of growth options increases with their idiosyncratic volatilities. This argument can be applied to explain the negative relation between idiosyncratic volatility and expected returns. Therefore, if they hold the same amount of growth options, assets with higher idiosyncratic volatility would provide a better hedge against aggregate uncertainty risk than those with lower idiosyncratic volatility, and consequently they would be more desirable assets and have lower risk premiums.

Ang, Hodrick, Xing, and Zhang (2006, 2009) show that exposures to aggregate volatility risk cannot explain the idiosyncratic volatility puzzle. However, I argue that aggregate uncertainty risk can account for the puzzle if we consider the interaction between uncertainty and growth options. In this paper, I test two hypotheses: (1) The

[8] I use the terms uncertainty and volatility interchangeably. There is no agreement on the direct measure of uncertainty, and popular proxies are the volatility of either stock returns or macro variables such as productivity, employment or output.

[9] The model with both time-varying aggregate and idiosyncratic uncertainty generates a value premium of about 4% while the model with only time-varying aggregate uncertainty generates that of about 2%.

idiosyncratic volatility discount is driven by growth stocks, and (2) Growth stocks with higher idiosyncratic volatility exhibit higher exposures to aggregate uncertainty risk.

To conduct empirical tests, I form 25 portfolios based on book-to-market ratio and idiosyncratic volatility, measured as the standard deviation of the residuals from the CAPM. [10] Weekly stock returns are used in order to match the results from empirical tests with those from model simulations. I rebalance portfolios annually based on the idiosyncratic volatility of the previous year. The results show that the differences in CAPM alphas between portfolios with low idiosyncratic volatility and those with high are significantly negative only for growth portfolios. In addition, they show that within growth portfolios, exposures to aggregate uncertainty risk, proxied by the VIX index, increase with idiosyncratic volatility. That is, growth portfolios with higher idiosyncratic volatilities have significantly lower exposures to aggregate uncertainty risk than those with lower idiosyncratic volatilities. I also find that growth portfolios with high idiosyncratic volatility tend to have higher investment rates, lower profitability, and more R&D expenditures. This finding is consistent with Hou, Xue, Zhang (2015a), which show that the investment and profitability factor loadings of the high-minus-low idiosyncratic volatility decile are both negative and significant.

I augment time-varying uncertainty into the investment-based asset pricing model and calibrate the model at a weekly frequency. Following Bloom (2009), uncertainty is defined as the standard deviation of aggregate and idiosyncratic productivity shocks.

[10] Ang, Hodrick, Xing and Zhang (2006, 2009) use the Fama-French three factor model to calculate idiosyncratic volatility. The idiosyncratic volatility from the CAPM is quantitatively similar and qualitatively identical to that from the three factor model. Ang, Hodrick, Xing and Zhang (2006, 2009) and other studies also show that the results from using the idiosyncratic volatility from the CAPM are consistent with those from using the idiosyncratic volatility from the three factor model.

The model is not a real-options model but generates the options by the interaction between non-convex adjustment costs and uncertainty. Non-convex adjustment costs are composed of the irreversibility of investment and fixed costs. Because these adjustment costs make investment mistakes more expensive, firms would be cautious and postpone their investment decisions when uncertainty is high (the 'wait-and-see effect'). This implies that the value of investment opportunities (growth options) increases with uncertainty, and therefore firms would want to keep their growth options rather than exercise them. In addition, investors would prefer assets with more growth options since those assets hedge the uncertainty risk. Such a positive impact of aggregate uncertainty risk on the value of growth options is magnified by idiosyncratic uncertainty, and this can explain why stocks with higher idiosyncratic volatility have lower average returns.

The model generates results consistent results with the empirical evidence. Using the model-generated data, I form 25 portfolios sorted on book-to-market ratio and idiosyncratic volatility, defined as the standard deviation of the residuals from the CAPM. Within growth portfolios the high-minus-low idiosyncratic portfolios have significantly negative CAPM alphas, while within value portfolios they do not. To investigate whether aggregate uncertainty risk can explain the idiosyncratic volatility discount that exists only within growth portfolios, I estimate the loadings on uncertainty risk of the 25 portfolios. The results show that within growth portfolios, the uncertainty risk loadings increase with idiosyncratic volatility while within value portfolios they do not. Therefore, the idiosyncratic volatility puzzle exists only in growth stocks, and aggregate uncertainty risk can account for the puzzle through its interaction with growth options, which is amplified by idiosyncratic volatility.

The remainder of this paper is organized as follows. In Section 2, I present the results from the empirical tests. In Section 3, I develop the investment-based asset pricing model with time-varying aggregate and idiosyncratic uncertainty. In Section 4, I calibrate the model and report the results from model simulations. In Section 5, I conclude.

2.2 Empirical Evidence

In this section, I begin by drawing plots using daily stock returns in order to explore the relations of idiosyncratic volatility with aggregate volatility, business cycles, and firm characteristics. Then I conduct a portfolio analysis using weekly stock returns in order to test whether aggregate volatility risk can explain the idiosyncratic volatility puzzle.

2.2.1 Data

The sample includes publicly traded U.S. firms for the 1963-2013 period. I use daily stock returns from the Center for Research in Security Prices (CRSP) and annual accounting data and firm characteristics from the COMPUSTAT annual fundamental files. The analysis is limited to common stocks (CRSP share codes 10 and 11) that are listed on NYSE, AMEX, or NASDAQ. Firms must also have accounting information in COMPUSTAT for at least two years to be included. Financial firms (sic codes between 6000 and 6999) and firms with negative book equity are excluded.

Idiosyncratic volatility is estimated using the capital asset pricing model (CAPM):

$$r_{it} = \beta_i^{MKT} MKT_t + \epsilon_{it}, \tag{2.1}$$

where where r_{it} is the excess return of stock i at time t, MKT_t is the market excess return and β_i^{MKT} is the loading of portfolio i on market risk. The estimate of idiosyncratic volatility is the monthly standard deviation of ϵ_{it}. I exclude stocks with less than 15 daily returns in estimating the model.

I use the VIX index as a proxy for aggregate uncertainty. The VIX is the implied volatility of the Standard & Poor's 500 portfolio, calculated from the prices of put and call options traded on the Chicago Board Options Exchange (CBOE). The data are taken from the CBOE, and the sample period is from January 1990 to December 2013. The monthly series of the VIX is calculated by averaging the daily values within each month.

2.2.2 Idiosyncratic Risk and Macroeconomy

Figure 2.1 plots the time-trend of the monthly average idiosyncratic volatility of the firms in the sample. The line represents the estimate of the average idiosyncratic volatility from equation (1), and the shaded vertical bars denote the NBER-dated recessions. The figure shows that idiosyncratic volatility tends to increase before and during recessions. The counter-cyclical movement of idiosyncratic volatility suggests that it would reflect macroeconomic risks.

Figure 2.2 compares the relation between monthly average idiosyncratic volatility and aggregate volatility, proxied by the VIX index. The solid line depicts the estimate of idiosyncratic volatility, and the dotted line represents the VIX. The figure shows that idiosyncratic volatility is highly correlated with aggregate volatility over the sample period. When aggregate volatility increases, idiosyncratic volatility also tends to increase. This finding implies that idiosyncratic volatility would be affected by aggregate volatility, which is a significant macroeconomic risk as shown in Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012).

2.2.3 Idiosyncratic Risk and Firm Characteristics

Figure 2.3 reports time-series variation of idiosyncratic volatility by firm characteristics. Panel A plots idiosyncratic volatility grouped by book-to-market ratio, and shows that there is no distinct pattern among the five portfolios. Panel B plots idiosyncratic volatility grouped by firm size, which is measured by market equity. It shows that smaller firms tend to have higher idiosyncratic volatilities than bigger firms. Since the correlation between size and idiosyncratic volatility is strong, I plot idiosyncratic volatility grouped by book-to-market ratio after controlling for size. Panel C reports the result. It shows that idiosyncratic volatility tends to decrease with book-to-market ratio except for the portfolio with the highest book-to-market ratio (the value portfolio). The idiosyncratic volatility of the value portfolio tends to be high especially during times of high idiosyncratic volatility.

2.2.4 Portfolio Analysis

To conduct the portfolio analysis, I sort stocks into 25 portfolios based on their book-to-market ratios and idiosyncratic volatilities. Weekly stock returns are used to match the results with the results from model simulations. The idiosyncratic volatilities of the 25 portfolios are estimated as the standard deviations of the residuals from the CAPM and are calculated after controlling for their size in order to eliminate the impact of size on idiosyncratic volatility. Portfolios are rebalanced annually based on the idiosyncratic volatilities of the previous year.

Table 2.1 reports the CAPM alphas of the 25 portfolios. It shows that the spread in abnormal returns between high and low idiosyncratic volatility portfolios is negative and significant for the first and second book-to-market quintiles while it is not significant for the other quintiles. Therefore, the idiosyncratic volatility discount exists only for portfolios with low book-to-market ratios.

Table 2.2 represents the loadings of the 25 portfolios on aggregate uncertainty risk. Aggregate uncertainty is proxied by the VIX index and the loadings are measured from the equation as follows:

$$r_{it} = \beta_0 + \beta_i^{MKT} MKT_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it}, \tag{2.2}$$

where MKT_t is the market excess return and β_i^{MKT} is the loading of portfolio i on market risk, and β_i^{VIX} is the loading of portfolio i on uncertainty risk. By adding MKT, I control for the effect of the market factor on cross-sectional returns. The table shows that within the growth portfolio, the uncertainty risk loadings increase with idiosyncratic volatility. Therefore, the spread of the risk loadings can account for the return difference between low and high idiosyncratic volatility portfolios.

To investigate the characteristics of the 25 portfolios, I estimate their investment rates, profitability, and research and development (R&D) expenditures. The investment rate is measured as the annual change in total assets (Compustat annual item AT) divided by 1-year-lagged total assets. The profitability is measured as ROE, which is income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity. R&D expenditures are calculated as R&D expenses (Compustat annual item XRD) divided by 1-year-lagged total assets. Table 2.3 reports the estimated values. Since the idiosyncratic volatility discount is driven mainly by the growth portfolio, my interpretation of the results focuses only on the growth portfolio. Panels A, B, and C show that within the growth portfolio, investment rates increase, profitability decreases, and R&D expenditures increase with idiosyncratic volatility. Therefore, if firms hold the same amount of growth options, those with higher idiosyncratic volatility tend to invest more, earn less profitability, and have more R&D expenditures than those with lower idiosyncratic volatility. This result is consistent with Hou, Xue, and Zhang (2015 a), which show that the investment and profitability factor loadings of the high-minus-low idiosyncratic volatility decile are both negative and significant.

2.3 The Model

I develop a dynamic investment model of heterogeneous firms with time-varying uncertainty. Two types of uncertainty, aggregate and idiosyncratic, are introduced into the model.

2.3.1 Production and Investment

The production function of firms is given by:

$$Y_{it} = X_t Z_{it} K_{it}^{\eta}, \tag{2.3}$$

At time t, a firm i produces output, Y_{it}, using physical capital, K_{it}. The productivity of a firm is composed of aggregate productivity, X_t, and firm-specific productivity, Z_{it}. The capital share, $0 < \eta < 1$, therefore, the production function decreases return to scale with capital.

Tomorrow's capital of firms is the sum of investment and leftover of today's capital after its depreciation.

$$K_{it+1} = I_{it} + (1-\delta)K_{it}, \qquad 0 < \delta < 1 \tag{2.4}$$

where I_{it} denotes firm investment, and δ represents the rate of capital depreciation.

2.3.2 Time-varying Uncertainty

I assume that both $x_t \equiv \log X_t$ and $z_{it} \equiv \log Z_{it}$ follow a first-order autoregressive process:

$$x_{t+1} = \bar{x}(1-\rho_x) + \rho_x x_t + \sigma_t^x \varepsilon_{t+1}^x, \tag{2.5}$$

$$z_{it+1} = \rho_z z_{it} + \sigma_t^z \varepsilon_{it+1}^z, \tag{2.6}$$

in which ε_{t+1}^x and ε_{it+1}^z are uncorrelated for all i, and ε_{it+1}^z and ε_{jt+1}^z are uncorrelated for any pair of i, j with $i \neq j$, $\bar{x}$ is the long-term mean of aggregate productivity, ρ_x and ρ_z are the persistence of aggregate and firm-level productivity, respectively.

Both the volatility of innovations to aggregate productivity, σ_t^x, and that to firm-specific productivity, σ_t^z, vary over time. They move based on a two-state Markov chain:

$$\sigma_t^x \in \{\sigma_L^x, \sigma_H^x\}, \tag{2.7}$$

$$\sigma_t^z \in \{\sigma_L^z, \sigma_H^z\}, \tag{2.8}$$

$$Pr(\sigma_{t+1} = \sigma_j \quad | \quad \sigma_t = \sigma_k) = \pi_{k,j}, \tag{2.9}$$

Time-varying volatility of aggregate productivity generates periods of low and high uncertainty in the economy while time-varying volatility of firm-specific productivity produces periods of low and high cross-sectional dispersion across firms. Since they are based on the same Markov process, periods of high economic uncertainty are accompanied by periods of high cross-sectional dispersion, and vice-versa.

2.3.3 Adjustment Costs

Each firm faces adjustment costs of investment whenever they change their current level of capital. The adjustment cost function is as fllows:

$$\Phi(I_{it}, K_{it}) = \begin{cases} a^{+}K_{it} + \frac{c}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} & \text{for } I_{it} > \delta K_{it} \\ 0 & \text{for } I_{it} = \delta K_{it} \\ a^{-}K_{it} + \frac{c}{2}\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} & \text{for } I_{it} < \delta K_{it} \end{cases} \tag{2.10}$$

Adjustment costs arise only from net investment, and replacing depreciated capital does not incur any costs. This formulation leads firms to pay the adjustment costs only when they deviate from the non-stochastic steady state of investment rate, δ.

2.3.4 Stochastic Discount Factor

The model is in a partial-equilibrium setting, and the stochastic discount factor is exogenously specified. The SDF follows as:

$$\log M_{t+1} = \log \beta - \gamma_x(x_{t+1} - x_t) - \gamma_{\sigma^x}(\sigma^x_{t+1} - \sigma^x_t), \tag{2.11}$$

where the subjective discount factor, $\beta > 0$, the price of risk for productivity shocks, $\gamma_x > 0$, and the price of risk for uncertainty shocks, $\gamma_{\sigma^x} < 0$.

The SDF is a function of productivity risk and uncertainty risk. The price of productivity risk, γ_x, is positive, while that of uncertainty risk, γ_{σ^x}, is negative.

2.3.5 Optimal Investment

The profit function for a firm is given by:

$$\Pi_{it} = Y_{it} - f, \tag{2.12}$$

where Y_{it} is output and f is the fixed costs of production, which must be paid by all the firms participating in operational activities.

Firms choose their investment activities to maximize the present value of their future cash flows, $V(K_{it}, Z_{it}; X_t, \sigma_t^x, \sigma_t^z)$. Optimal investment is defined as the solution to a dynamic optimization problem defined by the stochastic Bellman equation:

$$\begin{aligned} V(K_{it}, Z_{it}; X_t, \sigma_t^x, \sigma_t^z) &= \max_{I_{it}} \{\Pi_{it} - I_{it} - \Phi(I_{it}, K_{it}) \\ &+ E_t[M_{t+1} V(K_{it+1}, Z_{it+1}; X_{t+1}, \sigma_{t+1}^x, \sigma_{t+1}^z)]\} \qquad (2.13) \\ s.t. \quad & K_{it+1} = I_{it} + (1-\delta)K_{it} \qquad (2.14) \end{aligned}$$

where $V(\cdot)$ is the value function, Π_{it} is a profit function, I_{it} is investment, $\Phi(\cdot)$ is an adjustment cost function, E_t is the expectations operator, and M_{t+1} is the stochastic discount factor.

2.4 Quantitative Results

This section presents the quantitative results from the model. First, I discuss the calibration and evaluate whether the model can quantitatively capture the important features of the data. Then, I present the main results from model simulations.

2.4.1 Calibration

Table 2.4 reports parameter values used to calibrate the model. I calibrate the model at a weekly frequency. In total, 100 artificial samples are simulated; each sample has 5000 firms and 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions in the simulations and to match the length of the sample period with that in the empirical data.

The capital share, η, is chosen to be 0.6, which is close to the value estimated by Cooper and Ejarque (2001) and Hennessy and Whited (2007). The persistence of aggregate productivity, ρ_x, is set to be 0.996, which is converted from the quarterly estimate, 0.95, reported in Cooley and Prescott (1995) into a weekly value. I set the persistence of the firm-specific productivity as $\rho_z = 0.992$, which is converted into a weekly value from the quarterly estimate, 0.9, reported in Imrohoroglu and Tuzel (2013). The long-term average of aggregate productivity is set to be -5.2 to normalize the average long-term capital stock at unity. For fixed operating costs, I set $f = 0.001$ to match the median of the firm-level market-to-book-ratio of 1.64.

The transition probabilities for the uncertainty process, namely $\pi_{L,L}$ and $\pi_{H,H}$, are from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). They calibrate the quarterly transition probabilities as 0.95 and 0.92. I convert the values into weekly values and set as $\pi_{L,L} = 0.996$ and $\pi_{H,H} = 0.993$. The rate of depreciation, δ, is set to be 0.002, converted into a weekly value from the annual estimate reported in Cooper and Haltiwanger (2000).

The parameter for convex adjustment costs, c, is set to be 0.15 to match the annual volatility of the firm-level investment rates of 22.30%. The parameter for non-convex adjustment costs, a^+ and a^-, are set at 0.002 and 0.025 respectively, in order to match the median of the firm-level investment rates of 11.58%.

The subjective discount factor, β, is chosen to be 0.999 to match the average annual risk-free rates of 1.03%. I set the price of risk for productivity shocks to be $\gamma_x = 10$ and the price of risk for uncertainty shocks to be $\gamma_{\sigma^x} = -10$ to match the mean and volatility of market returns, which are 7.01% and 17.35% respectively, as well as the volatility of the risk-free rate of 2.31%.

The comparison between target moments from the data and those from model simulations is summarized in Table 2.5. The table shows that the averages of the risk-free rate and market return from model simulatoins are higher than those from the data. The volatilities of the risk-free rate and market return and the median and volatility of firm-level investment are closely matched. The median market-to-book ratio from model simulations are slightly lower than that from the data.

2.4.2 The Idiosyncratic Volatility Puzzle

I compute a model-implied VIX index and idiosyncratic volatility. The VIX is calculated as the expected conditional volatility of market returns, and the idiosyncratic volatility is computed as the standard deviation of the residuals from the CAPM using weekly returns. Figure 2.4 plots the relation between annual series of the VIX and average idiosyncratic volatility. The weekly-series of the VIX index are aggregated into an annual value by averaging the values for each year. The annual average idiosyncratic volatility is calculated by averaging idiosyncratic volatilities of firms in the sample for each year. The figure indicates that the two types of uncertainty tend to move together, which is consistent with the findings from the empirical data.

To do the same portfolio analysis done in the empirical tests in Section 2, I form 25 portfolios based on their book-to-market ratios and idiosyncratic volatilities. As in the empirical tests, the idiosyncratic volatilities are estimated as the standard deviations of the residuals from the CAPM and are calculated after controlling for their size. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on their idiosyncratic volatilities from the previous year. Table 2.6 reports the CAPM alphas of the 25 portfolios. It shows that within the first and second quintiles the high-minus-low idiosyncratic portfolios have significantly negative CAPM alphas, while within the other quintiles they do not. Therefore, the idiosyncratic volatility puzzle is only driven by portfolios with more growth options, which is consistent with the finding from the empirical data.

Next, I test whether aggregate uncertainty risk can explain the idiosyncratic volatility discount that exists in low book-to-market quintiles. I measure the loadings on the uncertainty risk from the equation as follows:

$$r_{it} = \beta_0 + \beta_i^{MKT} MKT_t + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it}, \tag{2.15}$$

where r_{it} is the excess return of portfolio i at time t, and $\Delta\sigma_t$ is the uncertainty shocks defined as the changes in the volatility of innovations to the aggregate productivity in the model. MKT is market excess returns, and β^{σ} and β^{MKT} are loadings on the uncertainty factor and the market factor, respectively. By adding MKT, I control for the effect of the market factor on cross-sectional returns. Table 2.7 reports the risk loadings on the uncertainty risk (β^{σ}) of the 25 portfolios. It shows that within the growth quintile, the portfolio with high idiosyncratic volatility has a higher risk loading than that with low idiosyncratic volatility. Therefore, the lower average return of the high idiosyncratic volatility portfolio can be explained by its higher loading on aggregate uncertainty risk since uncertainty risk has a negative risk price.

Lastly, I estimate the investment rates and profitability (ROE) of the 25 portfolios to see whether the model generates the similar portfolio characteristics to those from the empirical data. At the beginning of each period, capital level is pre-determined, and firms change the capital level by choosing their optimal investment during the period. The investment rate is calculated as the change in capital during the period divided by the capital level at the beginning of the period. Profitability is calculated as the net income (profits net of the adjustment costs of investment) divided by the value of market equity. Since the idiosyncratic volatility discount exists only in growth portfolios, my interpretation focuses on them. Panel A shows that investment rates increase with idiosyncratic volatility, and Panel B indicates that profitability decreases with idiosyncratic volatility. These results are consistent with those from the empirical evidence.

2.5 Conclusion

In this paper, I explore the relation between idiosyncratic volatility and cross-sectional returns. Specifically, I test two hypotheses: (1) The idiosyncratic volatility discount is driven by growth stocks, and (2) Growth stocks with higher idiosyncratic volatility exhibit higher exposures to aggregate uncertainty risk.

The empirical tests show that stocks with high idiosyncratic volatility have negative abnormal returns, which can not be explained by the CAPM, only if they have low book-to-market ratios. This finding suggests that the idiosyncratic volatility discount is driven mainly by growth stocks. To investigate whether uncertainty risk accounts for the idiosyncratic volatility discount, I regress the returns of 25 portfolios based on book-to-market ratio and idiosyncratic volatility on the uncertainty risk factor, controlling for the market risk. The results show that within growth portfolios, stocks with higher idiosyncratic volatility tend to have higher risk loading than those with lower idiosyncratic volatility. Therefore, the empirical tests provide evidence that aggregate uncertainty risk would account for the idiosyncratic volatility puzzle.

An investment-based asset pricing model with time-varying uncertainty generates results consistent with empirical evidence. The interaction between non-convex adjustment costs and uncertainty produces the time-varying value of growth options. Uncertainty has a positive impact on the value of the options since it expands the upside of possible outcomes. This positive impact is amplified by idiosyncratic volatility as shown in Koh (2014). Therefore, all else being equal, growth stocks with higher idiosyncratic volatility provide a better hedge against aggregate uncertainty risk than those with lower idiosyncratic volatility. This role of idiosyncratic volatility can explain its negative relation with expected returns.

2.6 Tables and Figures

Figure 2.1: **Idiosyncratic Volatility and Business Cycles**

This figure plots the monthly average idiosyncratic volatility of the firms in the sample from July 1963 to December 2013. Within each month, idiosyncratic volatility is estimated as the standard deviation of the residuals from the CAPM, and it is annualized in percent. The shaded vertical bars denote the NBER-dated recessions.

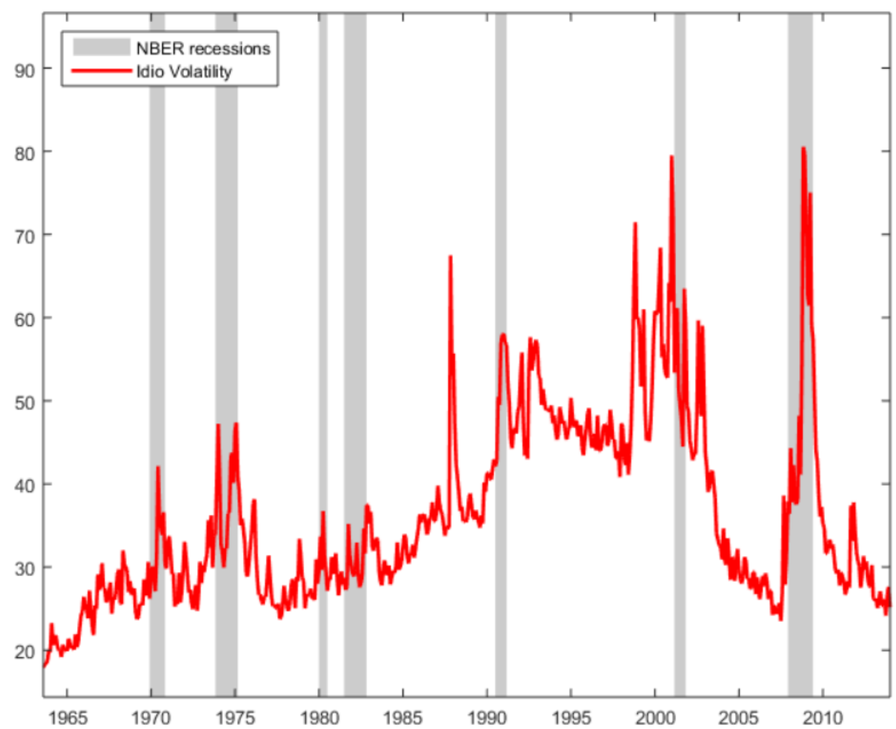


Figure 2.2: **Idiosyncratic Volatility and Aggregate Volatility**

This figure plots the relation between idiosyncratic volatility and aggregate volatility, proxied by the VIX index. Within each month, idiosyncratic volatility is estimated as the standard deviation of the residuals from the CAPM, and it is annualized in percent. The solid line represents idiosyncratic volatility, and the dotted line represents the monthly series of the VIX. The shaded vertical bars denote the NBER-dated recessions. The sample period is 1990 to 2013, restricted by the data availability of the VIX.

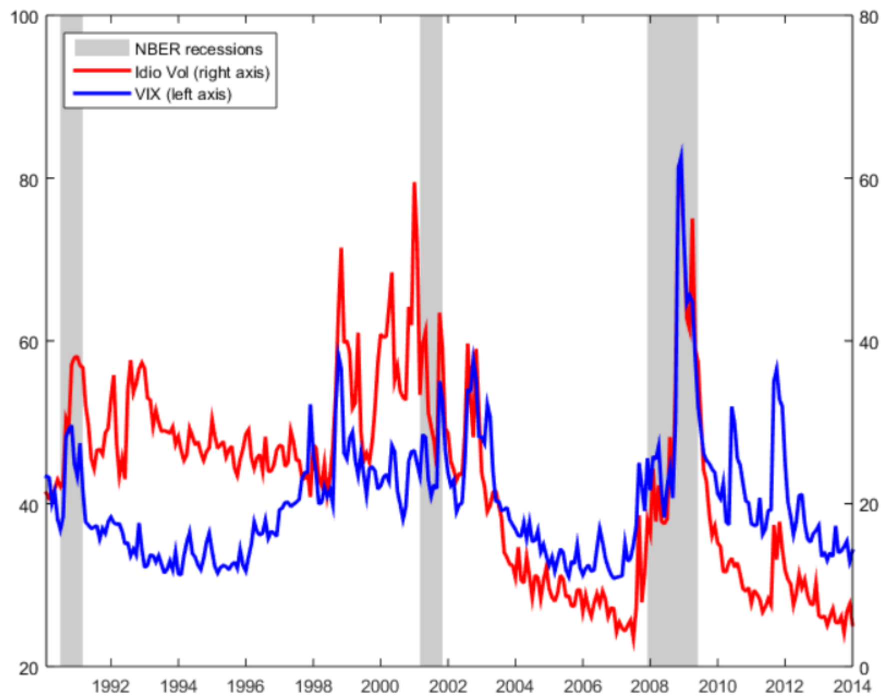


Table 2.1: **CAPM Alphas**

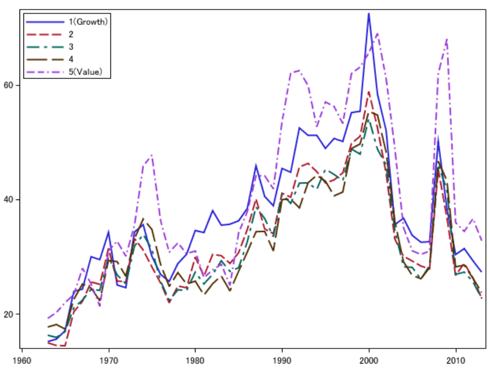
The table reports the CAPM alpha of 25 portfolios sorted by the book-to-market ratio and idiosyncratic volatility. Idiosyncratic volatility is measured as the standard deviation of the residuals from the CAPM. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on their idiosyncratic volatility of the previous year. The sample period is from 1963 to 2013. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	Value	V-G
Low IV	0.13	0.18	0.30	0.41	0.42	0.30
t-value	1.54	2.29	3.94	4.98	4.45	2.74
2	0.04	0.30	0.29	0.26	0.39	0.35
t-value	0.42	3.29	2.99	2.45	3.17	2.66
3	0.01	0.07	0.00	0.17	0.47	0.46
t-value	0.08	0.54	0.00	1.12	2.75	2.48
4	-0.35	0.05	0.21	0.42	0.70	1.05
t-value	-2.19	0.29	1.10	2.22	3.11	4.49
Hi IV	-0.73	-0.42	0.02	0.24	-0.01	0.72
t-value	-3.07	-1.72	0.06	0.86	-0.03	2.37
H-L	-0.86	-0.60	-0.28	-0.17	-0.43	0.42
t-value	-3.35	-2.30	-0.88	-0.61	-1.54	2.49

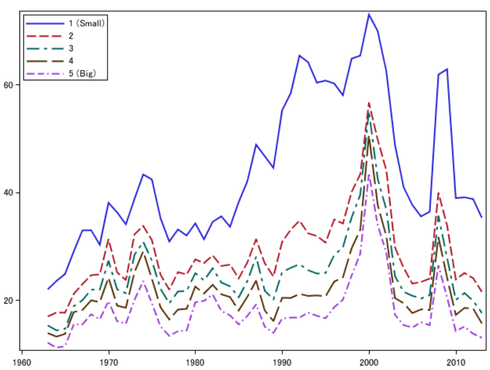
Figure 2.3: **Idiosyncratic Risk and Firm Characteristics**

This figure plots idiosyncratic volatility grouped by firm characteristics. Within each month, idiosyncratic volatility is estimated as the standard deviation of the residuals from the CAPM and is annualized in percent. Panel A shows idiosyncratic volatility averaged within the book-to-market quintile. Panel B shows idiosyncratic volatility averaged within the size (market equity) quintile. Panel C shows idiosyncratic volatility averaged within the book-to-market quintile after controlling for size.

(a) IVOL by Book-to-Market



(b) IVOL by Size



(c) IVOL by Book-to-Market controlling for Size

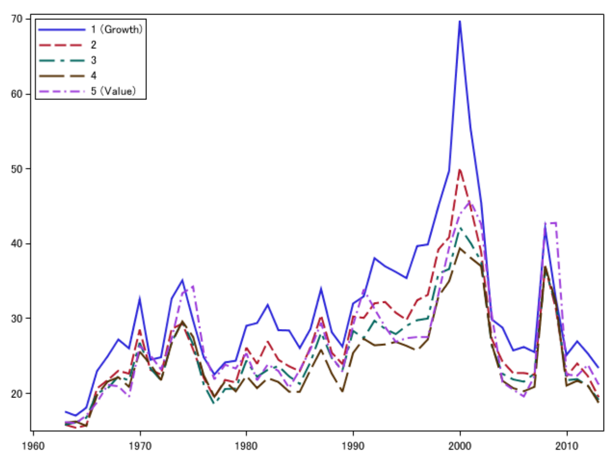


Table 2.2: **Sensitivities to Uncertainty Risk**

The table reports the uncertainty risk loadings (β^{VIX}) of 25 portfolios, sorted by the book-to-market ratio and idiosyncratic volatility. Aggregate uncertainty is proxied by the VIX index. Idiosyncratic volatility is measured as the standard deviation of the residuals from the CAPM. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on the idiosyncratic volatilities of the previous year. The sample period is from 1990 to 2013. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

The estimates are from the following equation:

$$r_{it} = \beta_0 + \beta_i^{MKT} MKT_t + \beta_i^{VIX} \Delta VIX_t + \epsilon_{it},$$

where MKT_t is the market excess return and β_i^{MKT} is the loading of portfolio i on market risk, and β_i^{VIX} is the loading of portfolio i on uncertainty risk.

	Growth	2	3	4	Value
Low IV	-0.13	-0.12	-0.15	-0.16	-0.17
t-value	-3.69	-3.26	-3.99	-3.93	-3.75
2	-0.14	-0.11	-0.19	-0.25	-0.22
t-value	-3.24	-2.42	-3.81	-4.34	-3.70
3	-0.08	-0.15	-0.31	-0.26	-0.21
t-value	-1.25	-2.46	-4.43	-3.21	-2.36
4	-0.02	-0.08	-0.23	-0.17	-0.21
t-value	-0.18	-0.91	-2.24	-1.67	-1.72
Hi IV	-0.02	-0.28	-0.16	-0.38	-0.12
t-value	-0.15	-1.95	-0.90	-2.39	-0.77

Table 2.3: **Portfolio Characteristics**

This table summarizes investment rate, profitability (ROE), and R&D expenditures of 25 portfolios sorted by the book-to-market ratio and idiosyncratic volatility. The investment rate is measured as the annual change in total assets (Compustat annual item AT) divided by 1-year-lagged total assets. The profitability is measured as ROE, which is income before extraordinary items (Compustat annual item IB) divided by 1-year-lagged book equity. R&D expenditures are calculated as R&D expenses (Compustat annual item XRD) divided by 1-year-lagged total assets. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on their idiosyncratic volatility of the previous year. The sample period is from 1963 to 2013.

	Growth	2	3	4	Value
	Panel A : Investment rate				
Low IV	1.26	1.01	0.82	0.64	0.41
2	2.39	1.48	1.11	0.77	0.39
3	3.55	1.70	1.14	0.79	0.28
4	3.88	1.44	1.25	0.59	0.07
Hi IV	3.55	1.04	0.68	0.40	-0.25
	Panel B : Profitability (ROE)				
Low IV	28.98	14.54	11.38	9.21	5.87
2	10.41	11.66	9.54	7.27	3.35
3	-66.25	7.22	6.35	4.30	0.24
4	-62.62	-0.91	-2.26	-2.66	-5.73
Hi IV	-221.58	-34.93	-25.65	-23.34	-21.52
	Panel C : R&D expenditures				
Low IV	4.42	3.00	2.54	2.20	1.91
2	6.82	4.16	3.52	3.21	2.55
3	10.54	6.59	5.30	4.60	3.28
4	13.93	9.05	7.73	6.32	4.50
Hi IV	18.59	13.20	11.09	9.34	6.66

Table 2.4: **Parameters**

This table reports the values for parameters used to calibrate the model. The model is calibrated at a weekly frequency.

Parameter	Notation	Value
Productivity		
Capital share	η	0.6
Persistence of aggregate productivity	ρ^x	0.999
Persistence of idiosyncratic productivity	ρ^z	0.992
Long-term average of aggregate productivity	$\bar{x}$	-5.2
Fixed operating costs	f	0.001
Uncertainty process		
Low volatility of aggregate productivity	σ^x_L	0.002
High volatility of aggregate productivity	σ^x_H	0.004
Low volatility of firm-specific productivity	σ^z_L	0.036
High volatility of firm-specific productivity	σ^z_H	0.072
Probability of staying in the low volatility state	$\pi_{L,L}$	0.996
Probability of staying in the high volatility state	$\pi_{H,H}$	0.993
Adjustment costs		
Depreciation rate	δ	0.002
Convex costs	c	0.15
Nonconvex costs of positive investment	a^+	0.002
Nonconvex costs of negative investment	a^-	0.025
Stochastic discount factor		
Subjective discount factor	β	0.999
Price of risk for productivity shocks	γ_x	10
Price of risk for uncertainty shocks	γ_{σ^x}	-10

Table 2.5: **Target Moments**

This table compares target moments from the data with those from model simulations. The model is calibrated at a weekly frequency. 100 samples are simulated, and each includes 5000 firms 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that of the empirical data. The moments from model simulations are aggregated to an annual level. The sample period of the empirical data is from 1963 to 2013. The firm-level data are taken from COMPUSTAT and the Center for Research in Security Prices (CRSP). The returns of book-to-market sorted portfolios, risk-free rates, and market returns are taken from Kenneth French's website.

	Data	Model
Average risk-free rate (%)	1.03	3.09
Volatility of risk-free rate (%)	2.31	2.52
Average market return (%)	7.01	10.08
Volatility of market return (%)	17.35	18.08
Median of firm-level investment rate (%)	11.58	12.00
Volatility of firm-level investment rate (%)	22.30	23.13
Median market-to-book ratio	1.64	1.41

Figure 2.4: **Idiosyncratic Volatility and Aggregate Volatility from the Model**

This figure plots the relation between model-generated idiosyncratic volatility and the VIX. Within each year, idiosyncratic volatility is estimated as the standard deviation of the residuals from the CAPM using weekly returns. The VIX is calculated as the expected conditional volatility of market returns. The solid line represents idiosyncratic volatility, and the dotted line represents the VIX. 100 samples are simulated, with each sample containing 5000 firms and 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that of the empirical data.

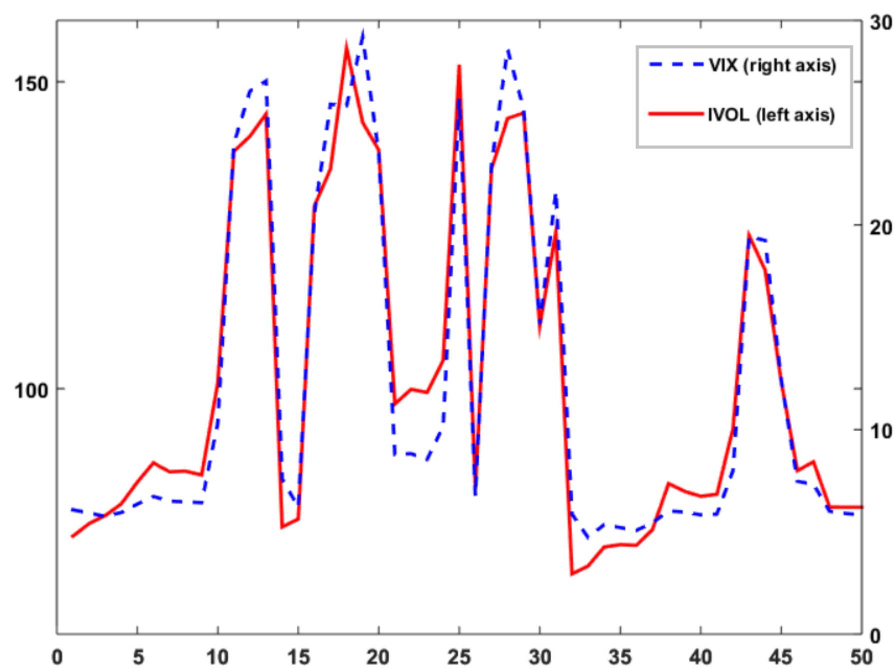


Table 2.6: **CAPM alphas from the Model**

The table reports the CAPM alphas of 25 portfolios from model simulations, sorted by book-to-market ratio and idiosyncratic volatility. Idiosyncratic volatility is measured as the standard deviation of the residuals from the CAPM. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on the idiosyncratic volatility of the previous year. 100 samples are simulated, with each sample containing 5000 firms and 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that of the empirical data. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

	Growth	2	3	4	Value	V-G
Low IV	0.77	0.60	0.42	1.23	1.01	0.24
t-value	4.36	3.61	2.82	6.45	3.74	1.06
2	-0.08	0.66	0.94	1.46	1.28	1.36
t-value	-1.69	5.00	5.47	8.34	5.13	2.01
3	-0.03	0.29	0.59	1.23	1.65	1.68
t-value	-0.53	2.71	4.46	6.85	5.71	2.24
4	-0.05	0.00	0.32	0.31	1.41	1.46
t-value	-2.42	-0.11	3.48	2.37	5.48	2.14
Hi IV	-0.07	0.00	-0.02	-0.02	1.58	1.65
t-value	-3.39	0.10	-0.48	-0.36	4.93	2.87
H - L	-0.84	-0.60	-0.44	-1.25	0.57	1.41
t-value	-3.85	-2.41	-1.58	-1.09	1.45	1.23

Table 2.7: **Sensitivities to Uncertainty Risk from the Model**

The table reports the uncertainty risk loadings (β^{σ}) of 25 portfolios from model simulations, sorted by book-to-market ratio and idiosyncratic volatility. Idiosyncratic volatility is measured as the standard deviation of the residuals from the CAPM. Weekly stock returns are used to calculate annual idiosyncratic volatility, and portfolios are rebalanced annually based on the idiosyncratic volatilities of the previous year. 100 samples are simulated, with each sample containing 5000 firms and 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that of the empirical data. Newey-West t-statistics are reported to control for heteroscedasticity and autocorrelation.

The estimates are from the following equation:

$$r_{it} = \alpha + \beta_i^{MKT} MKT_t + \beta_i^{\sigma} \Delta\sigma_t + \epsilon_{it},$$

where r_{it} is the excess return of portfolio i at time t and $\Delta\sigma_t$ is uncertainty shocks defined as the changes in the volatility of innovations to the aggregate productivity in the model. MKT is market excess returns, and β^{σ} and β^{MKT} are loadings on the uncertainty factor and the market factor, respectively.

	Growth	2	3	4	Value
Low IV	-0.03	-0.20	-0.11	-3.57	-4.06
t-value	-1.13	-1.50	-0.45	-1.85	-1.27
2	-0.58	0.75	0.47	-1.10	-5.35
t-value	-1.43	1.13	0.76	-0.62	-1.38
3	0.06	1.32	0.20	0.60	0.22
t-value	0.13	1.91	0.52	0.57	0.51
4	0.04	-0.10	-0.57	-0.43	-0.33
t-value	0.03	-0.26	-1.48	-2.12	-1.43
Hi IV	1.24	-0.18	-0.13	-0.25	-0.14
t-value	1.50	-1.09	-0.85	-2.18	-1.27

Table 2.8: **Portfolio Characteristics from the Model**

This table summarizes annual percent of investment rate and profitability (ROE) 25 portfolios, sorted by the book-to-market ratio and idiosyncratic volatility, from model simulations. The investment rate is measured as the change in capital divided by capital at the beginning of the period. The profitability is measured as ROE, which is net income divided by one-period lagged value of market equity. The estimated values are annualized in percent. 100 samples are simulated, with each sample containing 5000 firms and 5000 periods. The first 1400 periods are dropped to neutralize the impact of initial conditions on the simulation and to match the length of the sample period with that of the empirical data.

	Growth	2	3	4	Value
	Panel A : Investment rate				
Low IV	-0.36	0.45	0.16	0.38	-0.29
2	0.15	0.46	-0.18	0.00	0.00
3	0.16	0.19	0.34	0.10	0.21
4	2.61	3.31	0.49	0.53	0.62
Hi IV	4.86	3.62	2.48	3.42	2.27
	Panel B : Profitability (ROE)				
Low IV	17.66	16.02	16.24	13.16	7.62
2	17.98	16.39	14.94	12.45	10.37
3	17.66	15.78	14.16	12.12	8.04
4	16.82	14.16	13.09	10.27	8.68
Hi IV	15.73	13.81	12.08	10.13	8.22

Chapter 3: Historical q-Factors

3.1 Introduction

Hou, Xue, and Zhang (2015a, HXZ) propose the q-factor model that largely summarizes the cross section of average stock returns. The q-factor model says that the expected return of an asset in excess of the risk-free rate is described by the sensitivities of its returns to the market factor, a size factor, an investment factor, and a profitability (return on equity, ROE) factor:

$$E[R_i] - R_f = \beta^i_{\mathrm{MKT}}\, E[\mathrm{MKT}] + \beta^i_{\mathrm{ME}}\, E[r_{\mathrm{ME}}] + \beta^i_{\mathrm{I/A}}\, E[r_{\mathrm{I/A}}] + \beta^i_{\mathrm{ROE}}\, E[r_{\mathrm{ROE}}], \tag{3.1}$$

in which $E[R_i] - R_f$ is the expected excess return, $E[\mathrm{MKT}]$, $E[r_{\mathrm{ME}}]$, $E[r_{\mathrm{I/A}}]$, and $E[r_{\mathrm{ROE}}]$ are expected factor premiums, and β^i_{MKT}, β^i_{ME}, $\beta^i_{\mathrm{I/A}}$, and β^i_{ROE}, are the corresponding factor loadings.

In this paper, we hand-collect data on total assets and earnings from Moody's Industrial Manual to extend the sample for the q-factors back to 1926. We then compare the performance of the q-factor model with the Carhart (1997) model and the Fama-French (2015, FF) five-factor model, using a set of testing portfolios constructed with data in the long sample.

3.2 Factors

3.2.1 The Post-Compustat Sample

We describe the construction of the q-factors and the new FF factors.

The q-factor Model

The q-factors are constructed from a triple two-by-three-by-three sort on size, investment-to-assets (I/A), and ROE. I/A is the annual change in total assets (Compustat annual item AT) divided by one-year-lagged total assets, and ROE is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity.[11]

At the end of June of each year t, we use the median NYSE market equity (stock price per share times shares outstanding from CRSP) to split NYSE, Amex, and NASDAQ stocks into two groups, small and big. Independently, at the end of June of year t, we break NYSE, Amex, and NASDAQ stocks into three I/A groups using the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of I/A for the fiscal year ending in calendar year $t-1$. Also, independently, at the beginning of each month, we sort all stocks into three groups based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of ROE. Earnings data in Compustat quarterly files are used in the monthly sorts in the months immediately after the most recent public earnings announcement dates

[11] Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (Compustat quarterly item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock. Our measure of the book equity is the quarterly version of the annual book equity measure in Davis, Fama, and French (2000).

(Compustat quarterly item RDQ). For a firm to enter the factor construction, we require the end of the fiscal quarter that corresponds to its announced earnings to be within six months prior to the portfolio formation month.

Taking the intersections of the size, I/A, and ROE groups, we form 18 portfolios. Monthly value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced monthly. The size factor (r_{ME}) is the difference (small-minus-big), each month, between the simple average of the returns on the nine small size portfolios and the simple average of the returns on the nine big size portfolios. Designed to mimic the common variation in returns related to I/A, the investment factor ($r_{\mathrm{I/A}}$) is the difference (low-minus-high), each month, between the simple average of the returns on the six low I/A portfolios and the simple average of the returns on the six high I/A portfolios. Finally, designed to mimic the common variation in returns related to ROE, the ROE factor (r_{ROE}) is the difference (high-minus-low), each month, between the simple average of the returns on the six high ROE portfolios and the simple average of the returns on the six low ROE portfolios.

HXZ (2015a) start their sample in January 1972, which is restricted by the limited coverage of earnings announcement dates and book equity in Compustat quarterly files. HXZ (2015b) extend the q-factors sample back to January 1967. To overcome the lack of coverage for quarterly earnings announcement dates, we use the most recent quarterly earnings from fiscal quarters ending at least four months prior to the portfolio formation month. To expand the coverage for quarterly book equity, we use book equity from Compustat annual files and impute quarterly book equity with clean surplus accounting. Whenever available we first use quarterly book equity from Compustat quarterly files. We then supplement the coverage for fiscal quarter four with book equity from Compustat annual files.[12] If both approaches are unavailable, we apply the clean surplus relation to impute the book equity. If available, we backward impute the beginning-of-quarter book equity as the end-of-quarter book equity minus quarterly earnings plus quarterly dividends.[13] Because we impose a four-month lag between earnings and the holding period month (and the book equity in the denominator of ROE is one-quarter-lagged relative to earnings), all the Compustat data in the backward imputation are at least four-month lagged relative to the portfolio formation month.

If data are unavailable for the backward imputation, we impute the book equity for quarter t forward based on book equity from prior quarters. Let $\mathrm{BEQ}_{t-j}, 1 \leq j \leq 4$, denote the latest available quarterly book equity as of quarter t, and $\mathrm{IBQ}_{t-j+1,t}$ and $\mathrm{DVQ}_{t-j+1,t}$ be the sum of quarterly earnings and quarterly dividends from quarter $t-j+1$ to t, respectively. BEQ_t can then be imputed as $\mathrm{BEQ}_{t-j} + \mathrm{IBQ}_{t-j+1,t} - \mathrm{DVQ}_{t-j+1,t}$. We do not use prior book equity from more than four quarters ago $(1 \leq j \leq 4)$ to reduce imputation errors. We start the sample in January 1967 to ensure that all the 18 benchmark portfolios from the triple sort on size, I/A, and ROE have at least ten firms.

[12]Following Davis, Fama, and French (2000), we measure annual book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if available. Otherwise, we use the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption value (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

[13]Quarterly earnings are income before extraordinary items (Compustat quarterly item IBQ). Quarterly dividends are zero if dividends per share (item DVPSXQ) are zero. Otherwise, total dividends are dividends per share times beginning-of-quarter shares outstanding adjusted for stock splits during the quarter. Shares outstanding are from Compustat (quarterly item CSHOQ supplemented with annual item CSHO for fiscal quarter four) or CRSP (item SHROUT), and the share adjustment factor is from Compustat (quarterly item AJEXQ supplemented with annual item AJEX for fiscal quarter four) or CRSP (item CFACSHR).

The FF Five-factor Model

FF (2015) propose a five-factor model:

$$R_{it} - R_{ft} = a_i + b_i \,\mathrm{MKT}_t + s_i \,\mathrm{SMB}_t + h_i \,\mathrm{HML}_t + r_i \,\mathrm{RMW}_t + c_i \,\mathrm{CMA}_t + e_{it}. \quad (3.2)$$

MKT, SMB, and HML are the market, size, and value factors that form the FF (1993) three-factor model. RMW (robust-minus-weak) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA (conservative-minus-aggressive) is the difference between the returns on diversified portfolios of low and high investment stocks.

FF (2015) measure (operating) profitability (OP) as revenues (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA, zero if missing), minus interest expense (item XINT, zero if missing) all divided by book equity for the fiscal year ending in calendar year $t-1$, following Novy-Marx (2013). We measure annual book equity as in Davis, Fama, and French (2000) (see footnote 12). FF measure investment (Inv) as the change in total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, divided by total assets from the fiscal year ending in $t-2$, $(\mathrm{TA}_{t-1}-\mathrm{TA}_{t-2})/\mathrm{TA}_{t-2}$.

FF (2015) construct their benchmark factors from July 1963 to December 2014 from double (2×3) sorts by interacting size with book-to-market (B/M), and separately, with OP and with Inv. The size breakpoint is NYSE median market equity, and the B/M, OP, and Inv breakpoints are their respective 30th and 70th percentiles for NYSE stocks. HML is the average of the two high B/M portfolio returns minus the average of the two low B/M portfolio returns. RMW is the average of the two high OP portfolio returns minus the average of the two low OP portfolio returns.

CMA is the average of the two low Inv portfolio returns minus the average of the two high Inv portfolio returns. Finally, SMB is the average of the returns on the nine small stock portfolios from the three separate 2×3 sorts minus the average of the returns on the nine big stock portfolios.

3.2.2 The Pre-Compustat Sample

To get a sense of the results, without going through the massive data collection from Moody's Industrial Manual, we can obtain the annual book equity data in the pre-Compustat sample are available on the Kenneth French's Web site. Dividends are obtained from CRSP stock event data set. Under the clean surplus relation, earnings can be computed as the sum of dividends and the change in book equity, $\Pi_{it} = D_{it} + (B_{it} - B_{it-1})$, in which Π_{it} is earnings over period t, D_{it} is dividends over the same period, and B_{it} is the book equity at the end of period t or at the beginning of period $t+1$. We can then measure ROE as Π_{it}/B_{it-1} and investment as $(B_{it} - B_{it-1})/B_{it-1}$. To construct the q-factors in the pre-Compustat sample, up to December 1966, we use annual sorts on size and investment but monthly sorts on (annual) ROE with a four-month lag. To construct the FF five factors in the pre-Compustat sample, up to June 1963, at the end of June of year t we measure OP with Π_{it-1}/B_{it-1} for the fiscal year ending in calendar year $t-1$. To measure their investment (Inv) at the end of June of t, we use $(B_{it-1} - B_{it-2})/B_{it-2}$. Their benchmark factor construction can then be implemented in the pre-Compustat sample.

3.3 Factor Regressions

We run horse races between the Carhart model, the FF five-factor model, and the q-factor model from 1926 to 1967. Table 3.1 reports the results. The market factor (MKT) is calculated as the value-weighted market return minus the one-month Treasury bill rate from CRSP, and SMB, HML, and UMD are obtained from Kenneth-French's website. Panel A shows that our size, investment, and ROE factors earn on average 0.28%, 0.15%, and 0.24% per month (t = 1.93, 1.57, and 2.36), respectively. It also shows that the ROE premiums cannot be captured by the FF three-factor model or the Carhart four-factor model and have significant alphas, 0.37% (t = 4.83) and 0.39% (t = 4.36), respectively. The FF five-factor model also cannot explain the premiums, and the alpha is 0.24% (t = 2.74).

Panel B of Table 3.1 represents the properties of the FF five-factor model. It shows that their SMB and HML have on average 0.35% and 0.42% per moth (t = 2.10 and 1.99) and averages of RMW and CMA are not significantly different from zero. The Carhart alphas of RMW and CMA are 0.26% (t = 3.26) and -0.15% (t = -1.68), respectively. More importantly, the q-factor model explains RMW and CMA returns, leaving insignificant alphas. Panel C shows that UMD earns on average 0.68% per month (t = 2.84). Differently from HXZ (2015a and 2015b), both the q-factor model and the FF five-factor model cannot capture the UMD return. Panel D reports correlation among the factors. It shows that the investment factor has a correlation of 0.62 and the ROE factor has a correlation of 0.54 with RMW.

3.4 Conclusion

In this study, we extend the sample period back to 1926 by introducing new data, Moody's Industrial Manual and compare the q-factor model and the Fama-French five factor model. We obtain the annual book equity data in the pre-Compustat sample, which are available on the Kenneth French's Web site. Under the clean surplus relation, we calculate earnings using dividends and book equity. The results show that the q-factors have better properties than the Fama-French five factors. The q-factors cannot be captured by the Fama-French five factor model while the five factor model can be captured by the q-factor model, which is consistent with Hou, Xue, and Zhang (2015 b). Our next step is to manually collect total assets and earnings from Moody's Industrial Manual and compare the two models' performance in explaining anomalies.

3.5 Tables

Table 3.1: **Empirical Properties of the New Factors, July 1928 to December 1966**

r_{ME}, $r_{I/A}$, and r_{ROE} are the size, investment, ROE factors in the q-factor model, respectively. We calculate MKT as the value-weighted market return minus the one-month Treasury bill rate from CRSP. SMB, HML, RMW, and CMA are the size, value, profitability, and investment factors from the FF five-factor model (from 2×3 sorts), respectively. The data for SMB and HML in the three-factor model, SMB, HML, RMW, and CMA in the five-factor model, as well as UMD are from Kenneth French's Web site. m is the average return, α is either the FF three-factor alpha or the Carhart alpha, α_q the q-model alpha, a is the five factor alpha, and b, s, h, r, and c are five-factor loadings. The numbers in parentheses in Panels A to C are heteroscedasticity-and-autocorrelation-adjusted t-statistics, which test that a given point estimate is zero. In Panel D, the numbers in parentheses are p-values testing that a given correlation is zero.

Table 3.1: continued

Panel A: The q-factors							
	m	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2
r_{ME}	0.28	0.00	-0.00	0.80	0.12		0.84
	(1.93)	(0.03)	(-0.16)	(15.45)	(5.92)		
		0.01	-0.00	0.80	0.12	-0.01	0.84
		(0.14)	(-0.25)	(15.36)	(5.00)	(-0.34)	
$r_{I/A}$	0.15	0.05	0.03	0.06	0.15		0.15
	(1.57)	(0.58)	(0.79)	(0.99)	(2.96)		
		0.05	0.03	0.06	0.14	-0.00	0.15
		(0.61)	(0.74)	(0.99)	(2.85)	(-0.18)	
r_{ROE}	0.24	0.37	0.04	-0.15	-0.21		0.21
	(2.36)	(4.38)	(1.43)	(-1.95)	(-3.43)		
		0.39	0.04	-0.15	-0.22	-0.02	0.22
		(4.36)	(1.26)	(-1.98)	(-4.32)	(-0.68)	
	a	b	s	h	r	c	R^2
r_{ME}	-0.00	-0.01	0.83	0.03	0.08	0.05	0.87
	(-0.04)	(-0.71)	(17.21)	(1.08)	(1.05)	(0.66)	
$r_{I/A}$	0.12	0.07	0.03	-0.05	0.13	0.7	0.42
	(1.66)	(2.50)	(0.52)	(-1.21)	(1.21)	(7.41)	
r_{ROE}	0.24	0.11	-0.13	-0.03	0.63	0.28	0.36
	(2.74)	(3.27)	(-1.26)	(-0.40)	(3.95)	(2.71)	

(continued)

Table 3.1: continued

Panel B: The FF five factors							
	m	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2
SMB	0.35	-0.02	0.02	0.95	0.15	0.01	0.95
	(2.10)	(-0.42)	(2.29)	(48.43)	(8.87)	(0.60)	
HML	0.42	-0.06	0.04	0.04	1.03	-0.02	0.93
	(1.99)	(-1.03)	(2.31)	(1.04)	(41.56)	(-1.07)	
RMW	-0.01	0.26	-0.06	-0.05	-0.46	-0.00	0.60
	(-0.07)	(3.26)	(-1.80)	(-0.80)	(-12.25)	(-0.07)	
CMA	-0.02	-0.15	-0.05	0.04	0.35	-0.00	0.36
	(-0.15)	(-1.68)	(-1.21)	(1.06)	(7.43)	(-0.15)	
		α_q	β_{MKT}	β_{ME}	$\beta_{I/A}$	β_{ROE}	R^2
SMB		0.08	0.05	0.99	-0.05	-0.19	0.90
		(1.36)	(4.26)	(25.21)	(-1.30)	(-5.09)	
HML		0.25	0.27	0.24	0.66	-0.79	0.57
		(1.59)	(3.63)	(3.02)	(3.61)	(-9.09)	
RMW		0.00	-0.13	0.05	-0.80	0.77	0.76
		(0.00)	(-4.76)	(0.60)	(-8.66)	(10.60)	
CMA		0.04	-0.01	-0.08	0.86	-0.6	0.69
		(0.64)	(-0.28)	(-2.42)	(12.54)	(-13.41)	
Panel C: The Carhart momentum factor, UMD							
	m	α_q	β_{MKT}	β_{ME}	$\beta_{I/A}$	β_{ROE}	R^2
UMD	0.68	0.96	-0.34	-0.15	-0.31	0.27	0.28
	(2.84)	(5.30)	(-2.79)	(-1.01)	(-1.57)	(1.99)	
	a	b	s	h	r	c	R^2
UMD	1.04	-0.21	0.01	-0.5	-0.04	-0.03	0.38
	(6.10)	(-2.14)	(0.08)	(-2.65)	(-0.08)	(-0.07)	

(continued)

Table 3.1: continued

Panel D: Correlation matrix								
	$r_{I/A}$	r_{ROE}	MKT	SMB	HML	UMD	RMW	CMA
r_{ME}	0.31	-0.26	0.39	0.93	0.50	-0.32	-0.39	0.27
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$r_{I/A}$		0.19	0.28	0.24	0.37	-0.24	-0.52	0.62
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
r_{ROE}			-0.17	-0.37	-0.43	0.18	0.54	-0.41
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MKT				0.45	0.58	-0.50	-0.53	0.25
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB					0.54	-0.34	-0.44	0.30
					(0.00)	(0.00)	(0.00)	(0.00)
HML						-0.57	-0.77	0.60
						(0.00)	(0.00)	(0.00)
UMD							0.46	-0.33
							(0.00)	(0.00)
RMW								-0.84
								(0.00)

Table 3.2: **List of Anomalies with Data Available in the Pre-Compustat Sample**

The anomalies are from five categories: (i) momentum; (ii) value-versus-growth; (iii) investment; (iv) profitability; and (v) trading frictions. For each variable, we list its symbol, brief description, and source in the academic literature. Appendix A details variable definition and portfolio construction.

Panel A: Momentum			
R6-1	Price momentum (6-month prior returns, 1-month holding period), Jegadeesh and Titman (1993)	R6-3	Price momentum (6-month prior returns, 3-month holding period), Jegadeesh and Titman (1993)
R6-6	Price momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993)	R6-12	Price momentum (6-month prior returns, 12-month holding period), Jegadeesh and Titman (1993)
R11-1	Price momentum (11-month prior returns, 1-month holding period), Fama and French (1996)	R11-3	Price momentum (11-month prior returns, 3-month holding period), Fama and French (1996)
R11-6	Price momentum (11-month prior returns, 6-month holding period), Fama and French (1996)	R11-12	Price momentum (11-month prior returns, 12-month holding period), Fama and French (1996)
I-Mom	Industry momentum, Moskowitz and Grinblatt (1999)		
Panel B: Value-versus-growth			
B/M	Book-to-market equity, Rosenberg, Reid, and Lanstein (1985)	D/P	Dividend yield, Litzenberger and Ramaswamy (1979)
Rev	Reversal, De Bondt and Thaler (1985)	E/P	Earnings-to-price, Basu (1983)
O/P	Payout yield, Boudoukh, Michaely, Richardson, and Roberts (2007)	NO/P	Net payout yield, Boudoukh, Michaely, Richardson, and Roberts (2007)
Panel C: Investment			
$g_{\triangle \mathrm{B}}$	Growth in book equity change	g_B	Book equity growth
g_I	$g_{\triangle \mathrm{B}}$ prior to 1967, investment growth afterward, Xing (2008)	I/A	g_B prior to 1967, assets growth afterward, Cooper, Gulen, and Schill (2008)
CEI	Composite issuance, Daniel and Titman (2006)	NSI	Net stock issues, Pontiff and Woodgate (2008)
Panel D: Profitability			
ROE	Return on equity, Haugen and Baker (1996)		
Panel E: Trading frictions			
Tvol	Total volatility, Ang, Hodrick, Xing, and Zhang (2006)	Ivol	Idiosyncratic volatility, Ang, Hodrick, Xing, and Zhang (2006)
S-Rev	Short-term reversal, Jegadeesh (1990)	1/P	1/share price, Miller and Scholes (1982)

3.6 Addendum : Variable Definition and Portfolio Construction

As noted, we construct two sets of testing deciles for each anomaly variable: (i) NYSE-breakpoints and value-weighted returns; and (ii) all-but-micro breakpoints and equal-weighted returns.

3.6.1 Momentum

This category includes R6-1, R6-3, R6-6, R6-12, R11-1, and I-Mom.

R6-1, R6-3, R6-6, and R6-12

At the beginning of each month t, we split all stocks into deciles based on their prior six-month returns from month $t-7$ to $t-2$. Skipping month $t-1$, we calculate monthly decile returns, separately, for month t (R6-1), month t to $t+2$ (R6-3), month t to $t+5$ (R6-6), and month t to $t+11$ (R6-12). The deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in, for instance, R6-6, means that for a given R6-6 decile in each month there exist six sub-deciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the sub-deciles returns as the monthly return of the R6-6 decile.

When equal-weighting the returns of price momentum portfolios with all-but-micro breakpoints and equal-weighted returns, we do not impose a separate screen to exclude stocks with prices per share below $5 as in Jegadeesh and Titman (1993). These stocks are mostly microcaps that are absent in the all-but-micro sample. Also, value-weighting returns assigns only small weights to these stocks, which do not need to be excluded with NYSE breakpoints and value-weighted returns.

R11-1, R11-3, R11-6, and R11-12

We split all stocks into deciles at the beginning of each month t based on their prior 11-month returns from month $t-12$ to $t-2$. Skipping month $t-1$, we calculate monthly decile returns for month t (R11-1), month t to $t+2$ (R11-3), month t to $t+5$ (R11-6), and month t to $t+11$ (R11-12). The deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in, for instance, R11-6, means that for a given R11-6 decile in each month there exist six sub-deciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the sub-deciles returns as the monthly return of the R11-6 decile. Because we exclude financial firms, these decile returns are different from those posted on Kenneth French's Web site. When equal-weighting the returns of these portfolios with all-but-micro breakpoints and equal-weighted returns, we do not impose a separate screen to exclude stocks with prices per share below $5 as in Jegadeesh and Titman (1993). These stocks are mostly microcaps that are absent in the all-but-micro sample. Also, value-weighting returns assigns only small weights to these stocks, which do not need to be excluded with NYSE breakpoints and value-weighted returns.

I-Mom

We start with the FF (1997) 49-industry classifications. Excluding financial firms from the sample leaves 45 industries. At the beginning of each month t, we sort industries based on their prior six-month value-weighted returns from $t-6$ to $t-1$. Following Moskowitz and Grinblatt (1999), we do not skip month $t-1$ when measuring industry momentum. We form nine portfolios ($9 \times 5 = 45$), each of which contains five different industries. We define the return of a given portfolio as the simple average of the five industry returns within the portfolio. We calculate value-weighted (and equal-weighted) returns for the nine portfolios for six months from t to $t+5$, and rebalance the portfolios at the beginning of $t+1$. For a given I-Mom portfolio in each month there exist six sub-portfolios, each of which is initiated in a different month in the prior six-month period. We take the simple average of the six sub-portfolio returns as the monthly return of the I-Mom portfolio.

3.6.2 Value-versus-Growth

This category includes six anomaly variables, B/M, D/P, Rev, E/P, O/P, and NO/P.

B/M

At the end of June of each year t, we split stocks into deciles based on B/M, which is the book equity for the fiscal year ending in calendar year $t-1$ divided by the ME (from Compustat or CRSP) at the end of December of $t-1$. We calculate monthly decile returns from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Following Davis, Fama, and French (2000), we measure book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item

PSTK) for the book value of preferred stock. In the pre-Compustat sample, we use the book equity data from Kenneth French's Web site.

D/P

At the end of June of each year t, we sort stocks into deciles based on their dividend yields, which are the total dividends paid out from July of year $t-1$ to June of t divided by the market equity (from CRSP) at the end of June of t. We calculate monthly dividends as the begin-of-month market equity times the difference between cum- and ex-dividend returns. Monthly dividends are then accumulated from July of $t-1$ to June of t. We exclude firms that do not pay dividends. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

Rev

To capture the De Bondt and Thaler (1985) long-term reversal (Rev) effect, at the beginning of each month t, we split stocks into deciles based on the prior returns from month $t-60$ to $t-13$. Monthly decile returns are computed for month t, and the deciles are rebalanced at the beginning of $t+1$. To be included in a portfolio for month t, a stock must have a valid price at the end of $t-61$ and a valid return for $t-13$. In addition, any missing returns from month $t-60$ to $t-14$ must be -99.0, which is the CRSP code for a missing price.

E/P

We split stocks into deciles based on E/P at the end of June of each year t. In the post-Compustat sample, E/P is calculated as income before extraordinary items (Compustat annual item IB) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from Compustat or CRSP) at the end of December of $t-1$. Stocks with negative earnings are excluded. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In the pre-Compustat sample, earnings is calculated as dividends plus the change in book equity. Dividends are the begin-of-month market equity times the difference between cum- and ex-dividend returns. The book equity data are from Kenneth French's Web site.

O/P and NO/P

As in Boudoukh, Michaely, Richardson, and Roberts (2007), total payouts are dividends on common stock (Compustat annual item DVC) plus repurchases. Repurchases are the total expenditure on the purchase of common and preferred stocks (item PRSTKC) plus any reduction (negative change over the prior year) in the value of the net number of preferred stocks outstanding (item PSTKRV). Net payouts equal total payouts minus equity issuances, which are the sale of common and preferred stock (item SSTK) minus any increase (positive change over the prior year) in the value of the net number of preferred stocks outstanding (item PSTKRV).

At the end of June of each year t, we sort stocks into deciles based on total payouts (O/P) (or net payouts, NO/P) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from Compustat or CRSP) at the end of December of $t-1$. We exclude firms with non-positive total payouts (zero net payouts). Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Because the data on total expenditure of common and preferred stocks start in 1971, the O/P (NO/P) decile returns start in July 1972.

3.6.3 Investment

This category includes six variables, $g_{\triangle \mathrm{B}}$, g_B, g_I, I/A, CEI, and NSI.

$g_{\triangle \mathrm{B}}$

The growth in book equity change is inspired by investment growth in Xing (2008). In the long sample, we use change in book equity to measure investment. Annual sorts as in Xing (2008).

g_B

The change in book equity scaled by one-year-lagged book equity. Annual sorts.

g_I

Following Xing (2008), in the post-Compustat sample, we measure investment growth, g_I, for the portfolio formation year t as the growth rate in capital expenditure (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. At the end of June of each year t, we split stocks into deciles based on IG, and calculate monthly decile returns from July of year t to June of $t+1$. In the pre-Compustat sample, we measure investment as change in book equity.

I/A

Following Cooper, Gulen, and Schill (2008), in the post-Compustat sample, we measure investment-to-assets, I/A, for the portfolio formation year t as total assets (Compustat annual item AT) for the fiscal year ending in calendar year $t-1$ divided by total assets for the fiscal year ending in $t-2$ minus one. At the end of June of each year t, we split stocks into deciles based on I/A, and calculate monthly decile returns from July of year t to June of $t+1$. In the pre-Compustat sample, we measure I/A as $\triangle$B/B.

CEI

Following Daniel and Titman (2006), we measure CEI as the growth rate in the market equity not attributable to the stock return, $\log(\mathrm{ME_t}/\mathrm{ME_{t-5}}) - r(t-5,t)$. For the portfolio formation at the end of June of year t, $r(t-5,t)$ is the cumulative log return on the stock from the last trading day of June in year $t-5$ to the last trading day of June in year t, and ME_t is the market equity on the last trading day of June in year t from CRSP. Equity issuance such as seasoned equity issues, employee stock option plans, and share-based acquisitions increase the composite issuance, whereas repurchase activities such as share repurchases and cash dividends reduce the composite issuance. At the end of June of each year t, we sort stocks into deciles on CEI, and calculate monthly decile returns from July of year t to June of year $t+1$.

NSI

Following FF (2008), at the end of June of year t, we measure net stock issues (NSI) as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ to the split-adjusted shares outstanding at the fiscal year ending in $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX). At the end of June of each year t, we assign all stocks into deciles based on NSI. We exclude firms with zero NSI. Monthly decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

3.6.4 Profitability

This category includes only one variable, ROE.

ROE

Monthly sorts as in the construction of the ROE factor. Measure ROE with clean surplus relation in the pre-Compustat sample as in the construction of the ROE factor.

3.6.5 Trading Frictions

This category includes four anomaly variables, including Ivol, Tvol, S-Rev, and 1/P.

Ivol

Following Ang, Hodrick, Xing, and Zhang (2006), we measure a stock's Ivol as the standard deviation of the residuals from regressing the stock's returns on the FF (1993) three factors. At the beginning of each month t, we sort stocks into deciles based on the Ivol estimated with daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

Tvol

Following Ang, Hodrick, Xing, and Zhang (2006), we measure a stock's Tvol as the standard deviation of its daily returns. At the beginning of each month t, we sort stocks into deciles based on the Tvol estimated with the daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

S-Rev

To construct the Jegadeesh (1990) short-term reversal (S-Rev) deciles, at the beginning of each month t, we sort stocks into deciles based on the return in month $t-1$. To be included in a decile in month t, a stock must have a valid price at the end of month $t-2$ and a valid return for month $t-1$. Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

1/P

At the beginning of each month t, we sort stocks into deciles based on the reciprocal of the share price (1/P) at the end of month $t-1$. We calculate decile returns for the current month t and rebalance the deciles at the beginning of month $t+1$.

References

Abel, Andrew B., 1983, Optimal investment under uncertainty, *American Economic Review* 73(1), 228–233.

Abel, Andrew B., and Janice C. Eberly, 1996, Optimal investment with costly reversibility, *Review of Economic Studies* 63(4), 581–593.

Adrian, Tobias, and Joshua Rosenberg, 2008, Stock returns and volatility: pricing the short-run and long-run components of market risk, *Journal of Finance* 63, 2997–3030.

Ai, Hengjie. and Dana Kiku, 2013, Growth to value: Option exercise and the cross-section of equity returns, *Journal of Financial Economics* 107, 325–249.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 2009: 1-23.

Arellano, Cristina, Yan Bai, Patrick Kehoe, 2012, Financial market and fluctuations in volatility, Federal Reserve Bak of Minneapolis Research Department Staff Report 466.

Bachmann, Rudi and Giuseppe Moscarini, 2011, Business cycles and endogenous uncertainty, Working paper, Yale University.

Bachmann, Rudi, Steffen Elstner, and Erik Sims (2010), Uncertainty and economic activity: Evidence from business survey data. NBER Working Paper 16143.

Baker, Scott R., and Nicholas Bloom, 2011, Does uncertainty drive business cycles? Using disasters as natural experiment, NBER Working paper 19475.

Baker, Scott R., Nicholas Bloom, Steven J. Davis, 2013, Measuring economic policy uncertainty, Working paper, Stanford University.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527–566.

Bansal, Ravi, and Amir Yaron, 2004, Risk for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Bansal, Ravi, Dana Kiku, Ivan Shaliastovich, and Amir Yaron, 2014, Volatility, the macroeconomy and asset prices, *Journal of Finance*, forthcoming.

Basu, Susanto and Brent Bundick, 2011, Uncertainty shocks in a model of effective demand, Working paper, Boston College.

Bekaert, Geert, Marie Hoerova and Marco Lo Duca, 2013, Risk, Uncertainty, and Monetary Policy, *Journal of Monetary Economics* 60(7).

Belo, Frederico, Xiaoji Lin, and Santiago Bazdresch, 2014, Labor hiring, investment, and stock return predictability in the cross section, *Journal of Political Economy* 122, 129–177.

Belo, Frederico, Xiaoji Lin, and Fan Yang, 2014, External equity financing shocks, financial flows, and asset prices, Working paper, The Ohio State University.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options and security returns, *Journal of Finance* 54, 1153–1607.

Bernanke, Ben, 1983, Irreversibility, uncertainty, and cyclical investment, *The Quarterly Journal of Economics* 98(1), 85–106.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The Capital Asset Pricing Model: Some empirical tests, in *Studies in the Theory of Capital Markets*, edited by Michael C. Jensen, New York: Praeger, 79–121.

Bloom, Nicholas, 2009, The impact of uncertainty shocks. *Econometrica* 77(3), 623–685.

Bloom, Nicholas, 2014, Fluctuations in Uncertainty, *Journal of Economic Perspectives* 28(2), 153–176.

Bloom, Nicholas, Stephen Bond, and John Van Reenen, 2007, Uncertainty and investment dynamics, *Review of Economic Studies* 74(2), 391–415.

Bloom, Nicholas, Max Floetotto, and Nir Jaimovich and Stephen J. Terry, 2012, Really uncertain business cycles. Working paper, Stanford University.

Boldrin, Michele, Lawrence J. Christiano, and Jonas D.M. Fisher, 2000, Habit persistence, asset returns and the business cycle. Working paper, Federal Reserve Bank of Minneapolis.

Boguth, Oliver and Lars-Alexander Kuehn, 2013, Consumption volatility risk, *The Journal of Finance* 68, 2589–2615.

Campbell, John Y., 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487–512.

Campbell, John Y., Christopher Polk, and Tuomo Vuolteenaho, 2010, Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns, *Review of Financial Studies* 23, 305–344.

Campbell, John Y., Stefano Giglio, Christopher Polk, and Robert Turley, 2013, An intertemporal CAPM with stochastic volatility, Working paper, Harvard University.

Campbell, John Y. and Tuomo Vuolteenaho, 2004, Bad Beta, Good Beta, *American Economic Review* 94, 1249–1275.

Carhart, Mark M. 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

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

Carr, Peter, and Liuren Wu, 2009, Variance risk premia, *Review of Financial Studies* 22, 1311–1341.

Chacko, George, and Luis Viceira, 2005, Dynamic consumption and portfolio choice with stochastic volatility in incomplete markets, *Review of Financial Studies* 18, 1369–1402.

Chen, Joseph, 2002, Intertemporal, CAPM and the cross-section of stock returns, Working paper,University of Southern California.

Christiano, Lawrence, Roberto Motto, and Massimo Rostagno, 2014, *American Economic Review* 104(1), 27–65.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209–237.

Cooley, Thomas F., and Edward C. Prescott, 1995, Economic growth and business cycles, in Thomas F. Cooley, ed. Frontiers of Business Cycle Research (Princeton University Press, Princeton, NJ).

Cooley, Thomas F., and Vincenzo Quadrini, 2001, Financial markets and firm dynamics, *American Economic Review* 91, 1286-1310.

Cooper, Ilan, 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment, *Journal of Finance* 61, 139–170.

Cooper, Russell W., and John C. Haltiwanger, 2006, On the nature of capital adjustment costs, *Review of Economic Studies* 73, 611-633.

Dixit, Avinash K., and Robert S. Pindyck, 1994, Investment Under Uncertainty (Princeton University Press, Princeton, NJ).

Fajgelbaum, Pablo, Edouard Schaal, and Mathieu Taschereau-Dumouchel, Uncertainty trap, NBER Working Paper No.19973.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

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

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics.*

Fernandez-Villaverde, Jesus, and Juan F. Rubio-Ramrez, 2010, Macroeconomics and volatility: data, model, and estimation, Working paper, University of Pennsylvania.

Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Juan Rubio-Ramirez, and Martin Uribe, 2011, Risk matters: the real effects of volatility shocks, *The American Economic Review* 101(6), 2530– 2561.

Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Keith Kuester and Juan Rubio-Ramirez, 2013, Fiscal volatility shocks and economic activity, Working paper, University of Pennsylvania.

Gilchrist, S., Jae W. Sim, and Egon Zakrajsek, 2014, Uncertainty, financial frictions, and investment dynamics, NBER Working Paper No. 20038.

Gomes, Joao F., 2001, Financing investment, *American Economic Review* 90, 1263–1285.

Gomes, Joao F., Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

Gomes, Joao F., Lucas Schmid, 2010, Levered returns, *Journal of Finance*, 65, 467–494

Gourio, Francoi, 2012, Disaster risk and business cycles,*The American Economic Review* 102(6), 2734–66.

Guiso, L. and G. Parigi, 1999, Investment and Demand Uncertainty, *Quarterly Journal of Economics*, 114, 185–227.

Hall, Robert E., 2004, Measuring factor adjustment costs, *The Quarterly Journal of Economics* 119, 899–927.

Hansen, Lars Peter, 2013, Uncertainty Outside and Inside Economics Models, Prize Lecture for 2013 Nobel Prize in Economic Sciences.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015a, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015b, A comparison of new factor models, working paper, The Ohio State University.

Kahle, Kathleen M. and René M. Stulz, 2013, Access to capital, investment and the financial crisis, *Journal of Financial Economics* 110, 280–299.

Khan, Aubhik, and Julia K. Thomas, 2008, Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica* 76(2), 395–436.

Kogan, Leonid, and Dimitris Papanikolaou, 2012, Economic activity of firms and asset prices. Working Paper, MIT Sloan School.

Leahy, John V., and Toni M. Whited, 1996, The effect of uncertainty on investment: Some stylized facts, *Journal of Money, Credit and Banking* 28(1), 64–83.

Lin, Xiaoji, and Lu Zhang, 2013, The investment manifesto, *Journal of Monetary Economics* 60, 351-366.

Liu, Jun, 2007, Portfolio selection in stochastic environments, *Review of Financial Studies* 20, 1–39.

McQuade, Timothy J., 2012, Stochastic volatility and asset pricing puzzles, Working paper, Stanford University.

Merton, Robert C.,1973, An intertemporal capital asset pricing model. *Econometrica* 41, 867–887.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483-510.

Merz, Monika, and Eran Yashiv, 2007, Labor and the market value of the firm, *The American Economic Review* 97, 1419–1431.

Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639–685.

Pastor, Lubos, and Pietro Veronesi, 2013, Political Uncertainty and Risk Premia, *Journal of Financial Economics* 110, 520–545.

Pyndick, Robert, 1991, Irreversibility, uncertainty, and investment, *Journal of Economic Literature* 29, 1110–1152

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, 11(3), 9–16.

Schaal, Edouard, 2012, Uncertainty, productivity and unemployment in the Great Recession, Unpublished manuscript, Federal Reserve Bank of Minneapolis.

Segal, Gill, Ivan Shaliastovich, and Amir Yaron, 2014, Good and bad uncertainty: macroeconomic and financial market implications, Unpublished paper.

Stattman, Dennis, 1980, Book values and stock returns, *The Chicago MBA: A Journal of Selected Papers* 4, 25–45.

Stein, Luke C. D., and Elizabeth Stone, 2012, The effect of uncertainty on investment, hiring, and R&D: causal evidence from equity options, Unpublished paper.

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