Idiosyncratic Volatility, Aggregate Volatility Risk, and the Cross-Section
of Returns

by

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Curriculum Vitae

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Abstract

The first chapter presents a simple real options model that explains why in cross-section high idiosyncratic volatility implies low future returns and why the value effect is stronger for high volatility firms. In the model, high idiosyncratic volatility makes growth options a hedge against aggregate volatility risk. Growth options become less sensitive to the underlying asset value as idiosyncratic volatility goes up. It cuts their betas and saves them from losses in volatile times that are usually recessions. Growth options value also positively depends on volatility. It makes them a natural hedge against volatility increases. In empirical tests, the aggregate volatility risk factor explains the idiosyncratic volatility discount and why it is stronger for growth firms. The aggregate volatility risk factor also partly explains the stronger value effect for high volatility firms. I also find that high volatility and growth firms have much lower betas in recessions than in booms.

In the second chapter I show that the aggregate volatility risk factor (the BVIX factor) explains the well-known underperformance of small growth firms. The BVIX factor also reduces the underperformance of IPOs and SEOs by 45% and makes it statistically insignificant. The BVIX factor is unrelated to the investment factor proposed by Lyandres, Sun, and Zhang (2007) and has similar explanatory power. The BVIX factor is more helpful than the investment factor in explaining stronger new issues underperformance for small firms and growth firms. The investment factor is better at capturing the change in the underperformance in event time. The BVIX factor is also successful in explaining low returns to high cumulative issuance firms and the stronger cumulative issuance puzzle for growth firms.

In the third chapter I show that the results in the first two chapters are robust to controlling for the interaction of leverage and idiosyncratic volatility and behavioral effects, to replacing market-to-book with investment, and to different ways of defining the BVIX factor and the idiosyncratic volatility discount. I also find that 15 to 20% of the anomalies in the first chapter are concentrated in the three days around earnings announcements, but this effect can be partly explained by the risk shift at the announcement.

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1 Idiosyncratic Volatility, Growth Options and the Cross-Section of Returns

1.1 Introduction

A recent paper by Ang, Hodrick, Xing, and Zhang (2006) (hereafter - AHXZ) finds that firms with high idiosyncratic volatility earn negative abnormal returns. The return differential between high and low volatility firms is around 13% per year. Meanwhile, the conventional wisdom says that, if anything, the relation between idiosyncratic volatility and future returns should be positive. In what follows, I call this puzzle the idiosyncratic volatility discount.

Another recent paper by Ali, Hwang, and Trombley (2003) finds that the value effect is about 6% per year larger for high idiosyncratic volatility firms. It poses a challenge to any risk-based story for the value effect. Any such story has to explain why the value effect is related to something that is seemingly not risk - idiosyncratic volatility.

My paper develops a real options model that provides a risk-based explanation for both puzzles. In my model, higher idiosyncratic volatility makes growth options less sensitive to the current value of the underlying asset. The beta of the underlying asset does not change with idiosyncratic volatility, so the response of the underlying asset value to a given market return stays the same. However, the lower growth options sensitivity to the value of the underlying asset means that the response of the growth options value to the same market return decreases with idiosyncratic volatility. That is, higher idiosyncratic volatility means lower beta of growth options.

My model also suggests a new macroeconomic hedging channel. In recessions, both aggregate volatility and idiosyncratic volatility increase¹. The increase in idiosyncratic volatility makes growth options betas smaller and mutes the increase in their risk premiums. Because a lower expected return means a higher current price, the value of growth options drops less as the bad news arrives if the idiosyncratic volatility of the underlying asset is higher.

¹See, e.g., Campbell, Lettau, Malkiel, and Xu, 2001

Higher volatility in bad times also means higher value of growth options. Hence, aggregate volatility increases in recessions mean higher returns for growth firms than for value firms. My model shows that this effect is also stronger for high volatility firms.

These two effects form what I call the idiosyncratic volatility hedging channel. In my model, this channel is stronger for high idiosyncratic volatility firms, which makes them good hedges against adverse business cycle shocks. The second part of the idiosyncratic volatility channel can also contribute to our understanding of why value firms are riskier than growth firms.

The idiosyncratic volatility hedging channel works through economy-wide changes in volatility. Therefore, I link it to the concept of aggregate volatility risk developed in Campbell (1993) and Chen (2002). The models in Campbell (1993) and Chen (2002) are the extensions of Merton (1973) Intertemporal CAPM (henceforth ICAPM). In the Campbell model, higher aggregate volatility implies higher future risk premium. The stocks that covary negatively with changes in aggregate volatility command a risk premium, because they lose value when the future is also turning bleak.

In the Chen model, investors care not only about future returns, but also about future volatility. Aggregate volatility increases imply the need to boost precautionary savings and to cut current consumption. The stocks that covary negatively with aggregate volatility changes again command a risk premium, but for a different reason. They lose value exactly when consumption is reduced to build up savings.

The pricing of aggregate volatility risk is empirically confirmed by AHXZ in the same paper that establishes the idiosyncratic volatility discount. The return differential between the firms with the most and the least negative covariance with expected aggregate volatility changes is about 12% per year.

The stronger idiosyncratic volatility hedging channel for high idiosyncratic volatility firms implies that these firms have the lowest exposure to aggregate volatility risk. Their expected returns increase the least and their prices drop the least as expected aggregate volatility goes up and a recession begins. Therefore, high volatility stocks provide additional consumption when future prospects become worse and the need for precautionary

savings increases.

The value effect is, by definition, the return differential between growth options firms and assets in place firms. In my model, idiosyncratic volatility diminishes the growth options market beta and their exposure to aggregate volatility risk, but has no impact on assets in place. Hence, the expected return differential between value firms and growth firms should be wider for high volatility firms. The new testable hypothesis is that the stronger value effect for high volatility firms can be explained by aggregate volatility risk. The important implication is that aggregate volatility risk partly explains the value effect.

In my model, the idiosyncratic volatility discount is created by the change in the risk of growth options. The larger is the relative value of growth options in the firm value, the higher is the impact of idiosyncratic volatility on the firm's risk. The new empirical hypothesis is that the idiosyncratic volatility discount is stronger for growth firms. The other empirical hypothesis is that aggregate volatility risk explains the difference in the idiosyncratic volatility discount between growth and value firms.

I start empirical tests by sorting firms on market-to-book and idiosyncratic volatility. As the model predicts, the idiosyncratic volatility discount starts at zero for value firms and monotonically increases with market-to-book.

I also run cross-sectional regressions of firm returns on lagged firm characteristics. In the cross-sectional regressions, the product of market-to-book and idiosyncratic volatility is negative and strongly significant. Adding the product flips the signs of idiosyncratic volatility and market-to-book. The first sign change confirms that the idiosyncratic volatility discount is absent for low market-to-book (value) firms and increases with market-to-book. The second sign change shows that the value effect is absent for low volatility firms and suggests that my model can potentially explain the observed part of the value effect.

I also find that controlling for idiosyncratic volatility in the cross-sectional regressions increases the size effect by about a half and makes it much more significant. It is quite intuitive, because small firms are usually high idiosyncratic volatility firms. The size effect predicts high returns to these firms, and the idiosyncratic volatility discount predicts just the opposite. Hence, not controlling for either of them weakens the estimate of the other.

In time-series tests, I use the ICAPM to explain the idiosyncratic volatility discount, the stronger idiosyncratic volatility discount for growth firms, and the stronger value effect for high volatility firms. To test the prediction of my model that the three idiosyncratic volatility effects are explained by aggregate volatility risk, I introduce an aggregate volatility risk factor similar to the one in AHXZ. I call it the BVIX factor. The BVIX factor is based on stock return sensitivity to changes in the CBOE VIX index. The VIX index measures the implied volatility of S&P 100 options. AHXZ show that changes in VIX are a good proxy for changes in expected aggregate volatility. I define the BVIX factor as the zero-cost portfolio long in firms with the most negative and short in firms with the most positive return sensitivity to changes in VIX.

I find that high volatility firms, growth firms, and especially high volatility growth firms have negative BVIX betas. Their BVIX betas are also significantly lower than the betas of low volatility, value, and low volatility value firms. It means that high volatility, growth, and especially high volatility growth firms are good hedges against aggregate volatility risk. Their value goes up when aggregate volatility increases and most stocks witness negative returns.

The ICAPM with the BVIX factor completely explains the idiosyncratic volatility discount and why it is stronger for growth firms. The BVIX factor also reduces the strong value effect for high volatility firms by about a third. I also corroborate the BVIX results by showing that conditional market betas of high volatility, growth, and especially high volatility growth firms are lower in recessions than in booms.

The BVIX factor has a broader use than explaining the effects of idiosyncratic volatility on returns. I show that the BVIX factor is priced for several portfolio sets. The ICAPM with BVIX successfully competes with the Fama-French model. In the second chapter, I also show that the BVIX factor explains the low returns to small growth firms, IPOs, and SEOs, which are the worst failures of the existing asset-pricing models.

The Merton (1987) model predicts a positive relation between idiosyncratic volatility and expected returns for risky assets. It does not contradict my model that predicts the opposite relation for common stock. Rather, my model emphasizes the option-like nature

of common stocks, which produces another effect in the opposite direction. Therefore, my model is consistent with the evidence supporting the Merton model for other risky assets².

My model is related to Veronesi (2000) and Johnson (2004). They show that parameter risk can negatively affect expected returns by lowering the covariance with the stochastic discount factor. Johnson (2004) also uses the idea that the beta of a call option is negatively related to volatility. In my paper, I take a broader definition of idiosyncratic risk. I show that it can affect expected returns even if there is no parameter risk. I also focus on growth options instead of focusing on leverage, as Johnson (2004) does. It allows me to study the relation between idiosyncratic volatility and the value effect.

My cross-sectional results in the empirical part are close to Ali, Hwang, and Trombley (2003). Ali et al. (2003) argue that idiosyncratic volatility is a proxy for limits to arbitrage and therefore the value effect should be stronger for high volatility firms. However, Ali et al. (2003) do not study the implications of this fact for the idiosyncratic volatility discount. They also fail to find that controlling for the product of market-to-book and idiosyncratic volatility in Fama-MacBeth regressions flips the signs of market-to-book and volatility.

The other empirical study close to my paper is AHXZ, which is the first to establish the idiosyncratic volatility discount and the pricing of aggregate volatility risk. My paper extends AHXZ by showing both theoretically and empirically that the idiosyncratic volatility discount is explained by aggregate volatility risk. I also extend AHXZ by linking the idiosyncratic volatility discount and aggregate volatility risk to growth options.

Several empirical studies (e.g., Malkiel and Xu, 2003) find positive relation between idiosyncratic volatility and future stock returns at the portfolio level. This evidence is not inconsistent with my model that studies the same relation at the firm level. Firm-level idiosyncratic volatility is diversified away at the portfolio level. The remaining portfolio-level idiosyncratic volatility is more likely to result from omitted common factors. Hence, the two idiosyncratic volatility measures are likely to be poor proxies for each other.

The possible applications of the ideas in the paper stretch far beyond explaining the

²Green and Rydqvist (1997) find a positive relation between idiosyncratic risk and expected returns for lottery bonds. Bessembinder (1992) and Mansi, Maxwell, and Miller (2005) find a similar relation for currency and commodity futures and corporate bonds, respectively.

idiosyncratic volatility discount. I show that high idiosyncratic volatility creates a hedge against aggregate volatility risk and means lower expected returns. Therefore, more information and less uncertainty about a firm can hurt, if it comes in the wrong place. The wrong place is any asset behind a valuable real option. This idea has important implications for the studies of the link between firm value and expected return on the one hand and information quality, accounting quality, disclosure, etc., on the other.

In addition, establishing the link between idiosyncratic volatility and risk opens the gate to rethinking the results of the studies that use idiosyncratic volatility as a proxy for limits to arbitrage. Abundant evidence that many anomalies are stronger for high volatility firms can mean that the anomalies are related to aggregate volatility risk.

The chapter proceeds as follows. Section 2 lays out the model and derives its empirical implications. Section 3 discusses the data sources and shows descriptive statistics. Section 4 and Section 5 test the cross-sectional and time-series implications of my model. Section 6 offers the conclusion. The proofs of the propositions in text are collected in Appendix.

1.2 The Model

1.2.1 Cross-Sectional Effects

Consider a firm that consists of growth options, P_t , and assets in place, B_t . The growth options are represented by a European call option, which gives the right to receive at time T S_T for price K . Both S_t , the price of the asset underlying the growth options, and B_t follow geometric Brownian motions:

$$dS_t = \mu_S S_t dt + \sigma_S S_t dW_S + \sigma_I S_t dW_I \quad (1)$$

$$dB_t = \mu_B B_t dt + \sigma_B B_t dW_B \quad (2)$$

The stochastic discount factor process is given by

$$d\Lambda_t = -r\Lambda_t dt + \sigma_\Lambda \Lambda_t dW_\Lambda \quad (3)$$

dW_I is the purely idiosyncratic component of S_t and is assumed to be uncorrelated with the pricing kernel and, for simplicity, with W_S and W_B , though relaxing the second

assumption will not change the results. I also assume for simplicity that there is no purely idiosyncratic component in B_t (relaxing this assumption also does not change anything).

dW_I represents firm-specific shocks to growth options value. While the part of dW_S that is orthogonal to the pricing kernel is also firm-specific, I need dW_I to be able to increase the variance of the firm-specific shocks without increasing the covariance of S_t with the pricing kernel.

I do not assume anything about the correlation between W_S and W_B . The underlying asset of growth options and assets in place in my model are driven by two different processes, but these processes can be highly correlated.

The no-arbitrage condition and the definition of the pricing kernel imply that

$$dB_t = (r + \pi_B)B_t dt + \sigma_B B_t dW_B \quad (4)$$

$$dS_t = (r + \pi_S)S_t dt + \sigma_S S_t dW_S + \sigma_I S_t dW_I \quad (5)$$

where $\pi_B = -\rho_{B\Lambda}\sigma_B\sigma_\Lambda$ and $\pi_S = -\rho_{S\Lambda}\sigma_S\sigma_\Lambda$ are the risk premiums. The idiosyncratic risk is not priced for the unlevered claim on the asset behind growth options and it will not be priced for assets in place if I assume that they also carry some purely idiosyncratic risk.

However, for growth options the idiosyncratic risk is priced:

Proposition 1. The value of the firm is given by

$$dV_t/V_t = (r + \pi_B - (\pi_B - \pi_S\Phi(d_1)\frac{S_t}{P_t})\cdot\frac{P_t}{V_t})dt + \Phi(d_1)\frac{S_t}{V_t}(\sigma_S dW_S + \sigma_I dW_I) + \sigma_B \frac{B_t}{V_t} dW_B \quad (6)$$

$$\text{where } d_1 = \frac{\log(S/K) + (r + \sigma_S^2/2 + \sigma_I^2/2)(T - t)}{\sqrt{(\sigma_S^2 + \sigma_I^2) \cdot (T - t)}} \quad (7)$$

If assets in place are riskier than growth options, $\pi_B - \pi_S\Phi(d_1)S_t/P_t > 0$, then the expected rate of return to the firm (the drift in the firm value, μ_V) decreases in idiosyncratic risk, σ_I , and increases in the value of assets in place, B .

Proof: See Appendix A.

The intuition of the proof is that the idiosyncratic risk discount consists of two parts and relies on the existence of the value effect. First, an increase in idiosyncratic risk reduces the expected return by reducing elasticity of the growth options value with respect to the

underlying asset value ($\Phi(d_1)S_t/P_t$). Second, an increase in idiosyncratic risk increases the relative value of growth options (P_t/V_t) and makes the firm more growth-like, which decreases expected returns if the value effect exists.

By definition, the beta of the option is determined by, first, how responsive the underlying asset is to a percentage change in the risk factor and, second, how responsive the price of the option is to a percentage change in the price of the underlying asset. Hence, the beta of the option is equal to the product of the elasticity and the beta of the underlying asset. The elasticity decreases as volatility increases because if volatility is high, a change in the underlying asset price is less informative about its value at the expiration date. When idiosyncratic volatility goes up, the elasticity declines and the beta of the underlying asset stays constant, hence their product - the beta of growth options - decreases.

The idiosyncratic risk in my model is idiosyncratic at the level of the underlying assets, but its presence changes the systematic risk of growth options. If one pools the underlying assets, the risk will be diversified away, and this is the reason it is not priced for the unlevered claim on any of them. However, if one pools the underlying assets and then creates an option on them, the decrease in the idiosyncratic volatility will lead to the systematic risk of the option being greater than the systematic risk of the portfolio of separate options on each of the underlying assets.

The proof of Proposition 1 in Appendix A shows that in the current setup the sufficient (though not necessary) condition for the existence of the idiosyncratic volatility discount is that assets in place are riskier than growth options. There are currently two strands of the value effect literature that make this prediction. A good example of the first strand is Zhang (2005) that argues that assets in place are riskier in recessions because of costly divestiture. The second strand starts with Campbell and Vuolteenaho (2004) that shows that value firms have higher cash flow betas and growth firms have low cash flow betas, and the cash flow risk earns a much higher risk premium.

In Section 2.2 I also provide a new explanation of why growth options earn lower return than assets in place. The main idea there is that the volatility increase in the recession makes growth options more valuable. Holding all other effects fixed, the value

of growth options is therefore less negatively correlated with aggregate volatility. Growth options provide additional consumption when expected aggregate volatility is high and, consequentially, future investment opportunities are worse and the need for precautionary savings is higher. It makes growth options more desirable and their expected returns lower. In this subsection, however, I just assume a low risk premium for the underlying asset of growth options to keep things simple.

Corollary 1. Define $IVar$ as the variance of the part of the return generating process (6), which is orthogonal to the pricing kernel. Then the idiosyncratic variance $IVar$ is

$$\begin{aligned} IVar = & \sigma_S^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} \cdot (1 - \rho_{S\Lambda}^2) + \sigma_B^2 \cdot \frac{B^2}{V^2} \cdot (1 - \rho_{B\Lambda}^2) + \\ & + \sigma_I^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} + \sigma_S \cdot \sigma_B \cdot \Phi(d_1) \cdot \frac{S}{V} \cdot \frac{B}{V} \cdot (\rho_{SB} - \rho_{B\Lambda} \cdot \rho_{S\Lambda}) \end{aligned} \quad (8)$$

I show that for all reasonable parameter values σ_I

$$\frac{\partial IVar}{\partial \sigma_I} > 0, \quad (9)$$

which implies that my empirical measure of idiosyncratic volatility - the standard deviation of Fama-French model residuals - is a noisy but valid proxy for σ_I .

Proof: See Appendix A.

Corollary 1 shows that the idiosyncratic volatility depends positively on the idiosyncratic risk parameter. It is also impacted by some other factors, which means that it is a valid, although noisy, proxy for the idiosyncratic risk parameter. I do not claim that idiosyncratic volatility is the best proxy for idiosyncratic risk. All I need to tie my model to the data is that it is positively correlated with idiosyncratic risk, and Corollary 1 shows that it should be true.

Leaning on Corollary 1, in the rest of the section I use the terms "idiosyncratic volatility" and "idiosyncratic risk" interchangeably.

Corollary 2. The expected return differential between assets in place and growth options, $\pi_B - \pi_S \Phi(d_1) S_t / P_t$, is increasing in idiosyncratic risk.

Proof: Follows from the well-known fact that the option price elasticity with respect to the price of the underlying asset, $\Phi(d_1) S_t / P_t$, is decreasing in volatility.

Corollary 2 suggests a simple reason why in the rational world the value effect is higher for high volatility firms, as Ali et al. (2003) show. High volatility reduces the expected returns to growth options by reducing their elasticity with respect to the value of the underlying asset (and therefore reducing their beta) and leaves assets in place unaffected.

Corollary 2 implies that the observed value effect can wholly be an idiosyncratic volatility phenomenon. The return differential between growth options and assets in place can take different signs at different levels of idiosyncratic volatility. If the value effect is actually negative at zero idiosyncratic volatility, and positive at the majority of its empirically plausible values, the value effect will be on average positive even though growth options are inherently (absent idiosyncratic volatility) riskier than assets in place. In this case, the observed part of the value effect will be created only by the interaction between idiosyncratic volatility and growth options captured by my model.

Proposition 2. The effect of idiosyncratic volatility on returns, $\left| \frac{\partial \mu_V}{\partial \sigma_I} \right|$, is decreasing in the value of assets in place, B .

Proof: See Appendix A.

The main idea behind Proposition 2 is that without growth options or with very large B_t idiosyncratic volatility will not have any impact on returns. As growth options take a greater fraction of the firm, the impact of idiosyncratic volatility on returns becomes stronger, since it works through growth options. Also, more idiosyncratic volatility makes growth options less risky, while the risk of assets in place stays constant. It means a wider expected return spread between growth options and assets in place. The positive cross-derivative captures both effects.

The sign of the excess return derivative in Proposition 2 implies that in the cross-sectional regression the product of market-to-book and volatility is negatively related to future returns. In portfolio sorts Proposition 2 predicts large and significant idiosyncratic volatility discount for growth firms and no idiosyncratic volatility discount for value firms. Proposition 2 also predicts stronger value effect for high volatility firms.

Hypothesis 1. The cross-sectional regression implied by my model is

$$Ret \approx a - b \cdot M/B + c \cdot (M/B)_0 \cdot IVol - c \cdot M/B \cdot IVol + \delta Z, \quad a, c > 0 \quad (10)$$

where $(M/B)_0$ is the market-to-book ratio for the firm with no growth options and Z are other priced characteristics.

It implies that

$$\frac{\partial Ret}{\partial M/B} \approx -b - c \cdot IVol < 0 \quad (11)$$

$$\frac{\partial Ret}{\partial IVol} \approx -c \cdot (M/B - (M/B)_0) < 0 \quad (12)$$

I predict that in cross-sectional regressions the coefficient of idiosyncratic volatility, $c \cdot (M/B)_0$, is positive. The coefficient of the volatility product with market-to-book, c , is negative. The ratio of the coefficients equals to $(M/B)_0$, the market-to-book of the firm with no growth options. For the firm with no growth options, as (12) shows, the two terms cancel out and idiosyncratic volatility has no impact on returns. While the lowest possible market-to-book is 1 in my model, in Hypothesis 1 I replace 1 with an unknown $(M/B)_0$. $(M/B)_0$ is likely to be lower than 1, because book values lag market values and losses in the market value may be unrecognized in the book value for some time.

Equation (11) divides the observed value effect into two parts. The first one is denoted by b and represents the part of the value effect, which is unrelated to idiosyncratic volatility and comes from the difference in expected returns to assets in place and growth options absent idiosyncratic volatility. The second one is denoted $c \cdot IVol$ and represents the part of the value effect, which is driven by the interaction between growth options and idiosyncratic volatility. My model makes no prediction about the magnitude of the first part and even its sign.

The theoretical results in this section rely on the fact that growth options are call options on the projects behind them. In theory, any option-like dimension of the firm can be used to generate similar results, i.e. the idiosyncratic volatility discount that increases as the firm becomes more option-like. One well-known option-like dimension of the firm is leverage, which can replace growth options in the discussion above.

The motivation of looking at market-to-book rather than leverage is two-fold. First, using market-to-book in my model helps to explain the puzzling increase of the value effect with idiosyncratic volatility. The explanation will contribute to our understanding of the value effect. Second, the effects of idiosyncratic volatility on expected returns are stronger if the call option is closer to being in the money. For example, holding the value of growth options fixed, several at-the-money projects create stronger idiosyncratic volatility effects

than one deep-in-the-money project. The call option created by leverage is at the money when the firm is close to bankruptcy. Hence, growth options are usually closer to being at the money than the call option created by leverage. So, I expect growth options to be more important in understanding the idiosyncratic volatility discount.

Empirically, market-to-book and leverage are strongly inversely related. One reason is the mechanical correlation created by the market value being in the numerator of market-to-book and in the denominator of leverage. There are also several corporate finance theories predicting that growth firms should choose lower leverage (e.g., the free cash flow problem). Hence, in empirical tests the possible link between the idiosyncratic volatility discount and leverage should work against finding any relation between the idiosyncratic volatility discount and market-to-book.

1.2.2 The Idiosyncratic Volatility Hedging Channel

In the previous subsection I developed predictions about the impact of idiosyncratic volatility on the cross-section of returns. I derived from my model the three idiosyncratic volatility effects: the idiosyncratic volatility discount, the stronger idiosyncratic volatility discount for growth firms, and the higher value effect for high volatility firms. In this subsection, I sketch the ICAPM-type explanation of why the link between idiosyncratic volatility and expected returns cannot be captured by one-period models.

Campbell (1993) develops a model of aggregate volatility risk, where aggregate volatility increase means higher future risk premium. In Campbell (1993) the assets that react less negatively to aggregate volatility increases, offer an important hedge against adverse business-cycle shocks. These stocks earn a lower risk premium, because they provide consumption when future investment opportunities become worse.

Chen (2002) develops a model offering another reason why the assets that react less negatively to aggregate volatility increases can be valuable. In his model, investor care not only about future investment opportunities, but also about future volatility. An increase in expected aggregate volatility means the need to reduce current consumption in order to build up precautionary savings. The stocks that do not go down as aggregate volatility goes up provide consumption when it is most needed and therefore earn a lower risk premium.

My model goes further by predicting what types of firms will have the lowest, probably negative, aggregate volatility risk. I show that the presence of idiosyncratic volatility

and its close time-series correlation with aggregate volatility³ creates the economy-wide idiosyncratic volatility hedging channel that consists of two parts. One part comes from the impact of idiosyncratic volatility on expected returns, and the other comes from the impact of idiosyncratic volatility on the value of growth options. This subsection shows that the idiosyncratic volatility hedging channel makes the prices of high volatility, growth, and high volatility growth firms covary least negatively with aggregate volatility, which means lower exposure to aggregate volatility risk.

In unreported findings I show that the idiosyncratic volatility of low and high volatility firms respond to aggregate volatility movements by changing by the same percentage rather than by the same amount. Therefore, the key variable in the time-series dimension is the elasticity of risk premium with respect to volatility, instead of the derivative, which was the focus of the cross-sectional analysis in the previous subsection.

Proposition 3 The elasticity of the risk premium in my model decreases (increases in the absolute magnitude) as idiosyncratic volatility increases:

$$\frac{\partial}{\partial \sigma_I} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) < 0 \quad (13)$$

The elasticity of the risk premium in my model increases (decreases in the absolute magnitude) as the value of assets in place increases:

$$\frac{\partial}{\partial B} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) > 0 \quad (14)$$

The second cross-derivative of the elasticity with respect to idiosyncratic volatility and assets in place is positive:

$$\frac{\partial^2}{\partial \sigma_I \partial B} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) > 0 \quad (15)$$

Proof: See Appendix A.

Proposition 3 summarizes the first part of the idiosyncratic volatility hedging channel. As aggregate volatility increases, the future risk premium and idiosyncratic volatility also increase. The previous subsection shows that high idiosyncratic volatility means lower risk and lower expected returns. By Proposition 3, for high volatility firms the future risk premium goes up less than for low volatility firms. The impact on current stock prices is exactly opposite, because higher expected return means lower current price, all else

³See Campbell, Lettau, Malkiel, and Xu, 2001, and Goyal and Santa-Clara, 2003

equal. So, Proposition 3 implies that the stock prices of high volatility firms will react less negatively to aggregate volatility increases than the stock prices of low volatility firms. The identical reasoning can be repeated for growth firms and high volatility growth firms.

A 50% increase and even a 100% increase in idiosyncratic volatility is not uncommon in recessions (see e.g., Figure 4 in Campbell, Lettau, Malkiel, and Xu, 2001). The simulations in Appendix B show that the impact of such idiosyncratic volatility changes on the risk premium is substantial. In the simulations, the risk premium elasticity with respect to idiosyncratic volatility varies from zero for low volatility value firms to -0.5 for high volatility firms. It means that, net of any other effects of the recession on the risk premium, in recessions the idiosyncratic volatility hedging channel can reduce the expected returns to high volatility growth firms by a quarter or even a half.

Proposition 4 The elasticity of the firm value with respect to idiosyncratic volatility increases with idiosyncratic volatility:

$$\frac{\partial}{\partial \sigma_I} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) > 0 \quad (16)$$

The elasticity of the firm value decreases in the value of assets in place:

$$\frac{\partial}{\partial B} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) < 0 \quad (17)$$

The second cross-derivative of the elasticity with respect to idiosyncratic volatility and assets in place is negative:

$$\frac{\partial^2}{\partial \sigma_I \partial B} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) < 0 \quad (18)$$

Proof: See Appendix A.

Proposition 4 summarizes the second part of the idiosyncratic volatility hedging channel. As the economy enters the recession and volatility increases, the value of growth options, like the value of any option, tends to increase with volatility. This hedging channel is naturally stronger for growth firms, because their return is more affected by the changes in the growth options value. This is a new explanation of why growth firms are less risky than value firms.

Based on simulations, I conclude that this hedging channel is also stronger for high volatility firms than for low volatility firms and that it is the strongest for high volatility growth firms. The simulations also show that the firm value elasticity with respect to

idiosyncratic volatility is substantial. It varies from 0 for low volatility value firms to -0.3 and higher for high volatility growth firms. Therefore, net of any other cash flow effects of the recession, the increase in idiosyncratic volatility during the recession can increase the value of high volatility growth firms by 15-20%.

The bottom line of Propositions 3 and 4 is that high volatility, growth, and high volatility growth firms covary least negatively with changes in aggregate volatility. Hence, these three types of firms hedge against aggregate volatility risk. The reason is the idiosyncratic volatility channel, which predicts that the value of volatile growth options goes up the most as aggregate volatility and idiosyncratic volatility increase, and the expected risk premium of volatile growth options increases the least during volatile times.

Hypothesis 2. High idiosyncratic volatility firms, growth firms, and especially high idiosyncratic volatility firms hedge against aggregate volatility risk. Their betas with respect to the aggregate volatility risk factor are negative and lower than those of low volatility, value, and low volatility value firms.

The difference in the loadings on the aggregate volatility risk factor between high and low volatility firms should totally explain the idiosyncratic volatility effect and the stronger idiosyncratic volatility effect for growth firms. The aggregate volatility factor should also significantly contribute to explaining the value effect and why it is stronger for high volatility firms. In my empirical tests, leaning on Campbell (1993) and Chen (2002), I define the aggregate volatility factor as the zero-cost portfolio long in the firms with the lowest (most negative) return sensitivity to aggregate volatility increases and short in the firms with the highest (most positive) sensitivity.

I can also use Proposition 3 to test the hedging ability of high volatility, growth, and high volatility growth firms against adverse business-cycle shocks in a more conventional fashion. In the CAPM, lower risk premium means lower betas. Proposition 3 can be rephrased in terms of betas to show that in the conditional CAPM the betas of high volatility, growth, and high volatility growth firms are lower in recessions than in booms (details are available from the author). This hypothesis can be easily tested empirically.

Theoretically, the ICAPM is a more fruitful framework to explain the three idiosyncratic volatility effects than the conditional CAPM. The conditional CAPM assumes investors have no hedging demands and only care about the market risk. The idiosyncratic volatility hedging channel in the conditional CAPM is limited to the negative correlation

between the market beta and the market risk premium, which produces negative unconditional CAPM alphas for high volatility, growth, and high volatility growth firms.

Beyond that, in the ICAPM the hedging channel also means that these three types of firms provide additional consumption when it is most needed to increase savings. The reasons to increase savings after volatility increases are worse future investment opportunities and lower future consumption (Campbell, 1993) and higher future volatility and the precautionary motive (Chen, 2002). Also, the ICAPM captures the hedge coming from the fact that the value of growth options increases with volatility.

As in the previous subsection, the results in this subsection can be reformulated using any option-like dimension of the firm. The implication is that no matter which option-like dimension of the firm (market-to-book, leverage, etc.) is creating the idiosyncratic volatility discount, it should be explained by lower sensitivity of high volatility firms to negative business-cycle news and their lower risk in recessions.

1.3 Data and Descriptive Statistics

1.3.1 Data Sources

My data span the period between July 1963 and December 2006. Following AHXZ, I measure idiosyncratic volatility as the standard deviation of the Fama-French (1993) model residuals, which is fitted to daily data. I estimate the model separately for each firm-month, and compute the residuals in the same month. I require at least 15 daily returns to estimate the model and idiosyncratic volatility. I sort firms into idiosyncratic volatility quintiles at the end of each month using NYSE breakpoints and compute the returns over the next month using monthly return data from CRSP. Firms are classified as NYSE if the `exchcd` listing indicator from the CRSP events file at the portfolio formation date is equal to 1.

I do not include in my analysis utilities (SIC codes 4900-4999) and financials (SIC codes 6000-6999). I also include only common stock (CRSP codes 10 and 11). I construct the book-to-market ratio using the Compustat data, where the market value is defined as above and the book value is book equity (Compustat item #60) plus deferred taxes (Compustat item #74). The book value of deferred taxes is set to zero for firms that do not report it. To compute the market-to-book, I use the current year book value for firms with the fiscal year end in June or earlier or the previous year book value for firms with

later fiscal year end, to ensure that the book value is available before the date of portfolio formation.

I use monthly cum-dividend returns from CRSP and complement them by the delisting returns from the CRSP events file. Following Shumway (1997) and Shumway and Warther (1999), I set delisting returns to -30% for NYSE and AMEX firms (CRSP `exchcd` codes equal to 1, 2, 11, or 22) and to -55% for NASDAQ firms (CRSP `exchcd` codes equal to 3 or 33) if CRSP reports missing or zero delisting returns and delisting is for performance reasons. My results are robust to setting missing delisting returns to -100% or using no correction for the delisting bias.

I obtain the daily and monthly values of the three Fama-French factors and the risk-free rate from Kenneth French website at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>.

To measure the return sensitivity to changes in aggregate volatility, I use daily changes in the old version of the VIX index calculated by CBOE and available from WRDS. Using the old version of VIX gives a longer coverage starting with January 1986. The VIX index measures the implied volatility of the at-the-money options on S&P100. For a detailed description of VIX, see Whaley (2000) and AHXZ.

I measure the return sensitivity to changes in the VIX index by running each firm-month the regression of the daily excess returns to the stock on the daily excess returns to the market and the VIX change in this day. I require at least 15 non-missing returns in a firm-month for the estimation. The BVIX factor is then defined as the value-weighted return differential between the most negative and most positive VIX sensitivity quintile. AHXZ use the FVIX factor instead, which is the factor-mimicking portfolio tracking the VIX index. I use a simpler procedure to form my aggregate volatility risk factor because of estimation error concerns.

To estimate the conditional CAPM, I employ four commonly used conditioning variables: the dividend yield, the default premium, the risk-free rate, and the term premium. I define the dividend yield, (DIV_t) , as the sum of dividend payments to all CRSP stocks over the previous 12 months, divided by the current value of the CRSP value-weighted index. The default spread, (DEF_t) , is the yield spread between Moody's Baa and Aaa corporate bonds. The risk-free rate is the one-month Treasury bill rate, (TB_t) . The term spread, $(TERM_t)$, is the yield spread between ten-year and one-year Treasury bond. The

data on the dividend yield and the risk-free rate are from CRSP. The data on the default spread and the term spread are from FRED database at the Federal Reserve Bank at St. Louis.

In the tests of my model against behavioral stories I use two measures of limits to arbitrage - residual institutional ownership, $RInst$, and the estimated probability to be on special, $Short$, which proxies for the severity of short sale constraints. I define institutional ownership of each stock as the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. If the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero institutional ownership. Following Nagel (2004), I drop all stocks below the 20th NYSE/AMEX size percentile and measure residual institutional ownership for the remaining stocks as the residual from

$$\log\left(\frac{Inst}{1 - Inst}\right) = \gamma_0 + \gamma_1 \cdot \log(Size) + \gamma_2 \cdot \log^2(Size) + \epsilon \quad (19)$$

The estimated probability to be on special is defined as in D'Avolio (2002) and Ali and Trombley (2006)

$$Short = \frac{e^y}{1 + e^y}, \quad (20)$$

where

$$y = -0.46 \cdot \log(Size) - 2.8 \cdot Inst + 1.59 \cdot Turn - 0.09 \cdot \frac{CF}{TA} + 0.86 \cdot IPO + 0.41 \cdot Glam \quad (21)$$

Equation (21) uses the coefficients estimated by D'Avolio (2002) for a short 18-month sample of short sale data. Ali and Trombley (2006) use the same formula to estimate the probability to be on special for the intersection of Compustat, CRSP, and Thompson Financial populations. They show that the estimated probability is closely tied to other short sale constraint measures in different periods.

In (21) $Size$ is defined as shares outstanding times the price per share and measured in millions, $Inst$ is institutional ownership, $Turn$ is turnover, defined as the trading volume over shares outstanding, CF is cash flow⁴, TA are total assets (Compustat item #6), IPO is the dummy variable equal to 1 if the stock first appeared on CRSP 12 or less months ago, and $Glam$ is the dummy variable equal to 1 for three top market-to-book deciles.

⁴Following D'Avolio (2002) and Ali and Trombley (2006) I define cash flow as operating income before depreciation (Compustat item #178 plus Compustat item #14) less non-depreciation accruals, which are change in current assets (Compustat item #4) less change in current liabilities (Compustat item #5) plus change in short-term debt (Compustat item #34) less change in cash (Compustat item #1).

1.3.2 Descriptive Statistics

In Table 1 I report descriptive statistics across the idiosyncratic volatility quintiles formed using the previous month idiosyncratic volatility and rebalanced each month. Panel A looks at the quintiles formed using the breakpoints for the whole CRSP population. In my sample, I confirm the findings of AHXZ that the idiosyncratic volatility discount is about 1% per month in value-weighted returns and even more in the Fama-French abnormal returns. In equal-weighted returns, though, it is only present in the Fama-French (1993) abnormal returns. The equal-weighted abnormal return differential between the lowest and the highest volatility quintile is estimated at 0.6% per month, t-statistic 2.99, versus the value-weighted abnormal return differential of 1.32% per month, t-statistic 6.86. The weaker idiosyncratic volatility discount in equal-weighted returns is not surprising, because the idiosyncratic volatility discount runs against the size effect, which is much stronger in equal-weighted returns.

In the rest of the paper I will look at double sorts on idiosyncratic volatility and market-to-book. To keep all 25 portfolios balanced and non-negligible in terms of market cap percentage, I will use NYSE breakpoints to sort firms on both volatility and market-to-book. Therefore, in Panel B I look at idiosyncratic volatility quintiles that use NYSE breakpoints. Firms are classified as NYSE if the `exchcd` listing indicator from the CRSP events file is equal to 1. The `exchcd` indicator summarizes the listing history of the firm and reveals where the stock was listed at the portfolio formation date. It makes `exchcd` different from the `hexcd` listing indicator in the CRSP returns file, which reports the most recent listing. In Section 6.1 I show that using the `hexcd` indicator instead of `exchcd` creates a strong selection bias for the highest volatility firms. This bias contaminates the results in Bali and Cakici (2007) and explains why they find that the idiosyncratic volatility discount is not robust.

In Panel B the idiosyncratic volatility discount is smaller. It is absent in the raw returns, both equal-weighted and value-weighted, but is reliably present in the Fama-French alphas. The Fama-French alpha of the portfolio long in the lowest volatility quintile and short in the highest volatility quintile is 32 bp per month, t-statistic 2.22, for equal-weighted returns, and 59 bp per month, t-statistic 4.34, for value-weighted returns. It is twice smaller than what I get using CRSP breakpoints to form the quintiles, but still economically large and highly significant.

The fact that using NYSE breakpoints gives smaller values of the idiosyncratic volatility discount is not surprising. Both Panel A and Panel B show that the idiosyncratic volatility discount is driven primarily by the stocks in the highest volatility quintile. Because NYSE stocks are usually larger and less volatile, using NYSE breakpoints means pushing more stocks in the highest volatility quintile, and it depresses the idiosyncratic volatility discount.

In Panel C I estimate the Fama-French factor betas for each of the volatility quintiles (with NYSE breakpoints). I find that the market beta and the size beta strongly increase with volatility, and the HML beta strongly decreases with volatility, suggesting that the stocks in the highest volatility quintile are small and growth. It is confirmed in the last two rows of Panel C, which report size and market-to-book at the portfolio formation date. The highest volatility firms tend to be much smaller and have a much higher market-to-book than other firms.

1.4 Cross-Sectional Tests

1.4.1 Double Sorts

My model predicts that the idiosyncratic volatility discount increases with market-to-book and is absent for value firms. The prediction about the value effect is symmetric and implies that the value effect increases with idiosyncratic volatility. I first look at the 5-by-5 independent portfolio sorts on market-to-book and idiosyncratic volatility. The sorts are performed using NYSE (`exchcd=1`) breakpoints. The results are robust to using conditional sorting and/or CRSP breakpoints.

In Panel A of Table 2 I test these hypotheses for the Fama-French (1993) value-weighted abnormal returns. I use the formation month market capitalization for value-weighting. The Fama-French abnormal returns are defined as the alphas from separate time-series regressions fitted to each of the 25 portfolios. The results are robust to using raw returns or the CAPM alphas instead.

Panel A shows that the predictions of my model are strongly supported by the data. The magnitude of the idiosyncratic volatility discount monotonically increases with market-to-book from 10 bp per month (t-statistic 0.48) in the extreme value portfolio to 84 bp per month (t-statistic 3.92) in the extreme growth portfolio. The difference is highly signif-

icant with t-statistic 2.80. In terms of statistical significance, the idiosyncratic volatility discount is confined to the three top market-to-book quintiles.

A similar pattern is observed for the value effect. It starts with the negative Fama-French alpha of -27.5 bp per month (t-statistic -1.50) in the lowest volatility quintile, monotonically increases across the idiosyncratic volatility quintiles, and ends up with the Fama-French alpha of 46 bp per month (t-statistic 2.47) for the highest volatility quintile. The highest idiosyncratic volatility quintile is the only one in which the Fama-French model cannot fully explain the value effect.

Equal-weighted alphas in Panel B give a similar picture. If the returns are equal-weighted, the idiosyncratic volatility discount increases from -32.5 bp, t-statistic -1.81 in the value quintile to 65 bp, t-statistic 3.34, in the growth quintile. The growth quintile is the only market-to-book quintile with the significant idiosyncratic volatility discount in equal-weighted returns. The difference in the idiosyncratic volatility discount between value firms and growth firms is highly significant with t-statistic 4.92.

The unexplained part of the value effect also increases with idiosyncratic volatility from 23 bp, t-statistic 1.86, in the lowest volatility quintile to the astonishing 1.2%, t-statistic 8.23, in the highest volatility quintile. The Fama-French model cannot explain the value effect in equal-weighted returns in the top three idiosyncratic volatility quintiles.

The portfolio that seems to generate the majority of these effects and represents the worst failure of the Fama-French model is the highest volatility growth portfolio. In Panel A this portfolio witnesses the negative alpha of -56.5 bp, t-statistic -3.89, and earns the average raw return of 43 bp per month, very close to the average value of the risk-free rate in my sample. Such a low return to high volatility growth firms is totally consistent with my model. The model predicts that the firms with the highest volatility and the highest market-to-book should be the best hedges against aggregate volatility increases and should therefore earn the lowest expected return.

The bottom line of Table 2 is that the Fama-French model fails to explain the idiosyncratic volatility discount if market-to-book is high and it fails to explain the value effect if idiosyncratic volatility is high. The Fama-French model also fails to explain why the idiosyncratic volatility discount increases with market-to-book and why the value effect increases with idiosyncratic volatility. It proves the importance of the interaction between idiosyncratic volatility and growth options analyzed in my model.

1.4.2 Firm-Level Fama-MacBeth Regressions

To corroborate my findings in Table 2, I run firm-level Fama-MacBeth (1973) regressions in Table 3. In each month I regress the return to each firm on its market beta estimated using daily returns in the current month, and firm characteristics measured in the previous year. I use the percentage ranking of size, market-to-book and idiosyncratic volatility as the independent variables, because the untransformed variables are extremely skewed.

In the first three columns of Table 3 I make sure that the patterns already documented in the literature exist in my sample as well. I document the strong and significant size effect, value effect, and idiosyncratic volatility discount. I also show in the third column that the value effect is larger for high volatility firms.

In the fourth column I test the main prediction of my model by estimating the regression from Hypothesis 1. I regress returns on beta, size, market-to-book, idiosyncratic volatility, and the product of market-to-book and volatility. My model predicts that the coefficient of the product of market-to-book and volatility will be negative and highly significant. After I add the product, the sign of the coefficient on idiosyncratic volatility should change.

Table 3 shows that this prediction is strongly supported by the data. The product of market-to-book and volatility is extremely significant with t-statistic -6.31, and the idiosyncratic volatility has positive and insignificant coefficient. It means that the idiosyncratic volatility discount is absent for extreme value firms and is significantly increasing in market-to-book, which confirms my findings in Table 2.

The coefficient on market-to-book also changes the sign in the presence of its product with idiosyncratic volatility. It means that the interaction between growth options and idiosyncratic volatility predicted by my model can be strong enough to subsume the return effects usually attributed to either market-to-book or idiosyncratic volatility.

The magnitude of the coefficient on the interaction term suggests that its economic impact is large. From the estimates in the fourth column I predict that the idiosyncratic volatility discount will be $-(0.0016 \cdot (90 - 10) - 0.00024 \cdot (90 - 10) \cdot 10) = 0.07\%$ per month for extreme value firms (10% market-to-book percentile) and $-(0.0016 \cdot (90 - 10) - 0.00024 \cdot (90 - 10) \cdot 90) = 1.33\%$ per month for extreme growth firms (90% market-to-book percentile). The estimated strength of the idiosyncratic volatility discount for growth firms and its difference from the idiosyncratic volatility discount for value firms are larger than what I estimate in Table 2, because I use NYSE breakpoints there. When I use CRSP breakpoints

for the double sorts (results not reported), I estimate the idiosyncratic volatility discount, defined as the value-weighted Fama-French alpha, for the growth quintile at 1.73%, 1.46% difference from the value quintile, which is very close to the estimates from the cross-sectional regression.

Making further use of Hypothesis 1, I take the ratio of the coefficients on idiosyncratic volatility and its product with market-to-book to measure the percentage of firms with no growth options. The result implies that 6.6% of the firms in my sample have no growth options, which is quite plausible.

The first four columns in Table 3 use the current-month beta as the measure of the market risk. While factor models predict that returns are associated with current risk, not past risk, in the next four columns I check whether my results hold if I use the previous-month beta. Because beta and idiosyncratic volatility are positively correlated, but have opposing effects on returns, I expect that having a worse proxy for beta would make idiosyncratic volatility to pick up some beta effects and become weaker.

This is what I find in the sixth column - the lagged beta has the wrong and insignificant sign, the coefficient on idiosyncratic volatility decreases by a third, and its t-statistic becomes twice smaller as I replace the current beta with the lagged beta. This is the only thing that actually changes, and the results of my preferred regression in the rightmost column, which has all five regressors, are the same with the current beta and the lagged beta. Therefore I conclude that my results are robust to using lagged beta and the job of explaining the idiosyncratic volatility discount only becomes easier with it. I also experiment with using other definitions of beta and dropping it altogether, and the conclusion is the same.

Ali et al. (2003) run a similar regression in their Table 3 and find the right and significant sign on the product of volatility and market-to-book. They fail to find that adding the product on the left-hand side flips the signs of market-to-book and idiosyncratic volatility. The main difference between our research designs is that they use size-adjusted returns on the left-hand side of the regression. Keeping in mind the negative relation between the size effect and the idiosyncratic volatility discount, I suspect that the crude size adjustment they use can overstate the idiosyncratic volatility discount.

Controlling for idiosyncratic volatility increases the magnitude and significance of the size effect. The slope of the size variable increases by 50% and the t-statistic nearly doubles

when I compare the first column of Table 3 with any other column. This result is driven by the negative correlation between size and idiosyncratic volatility. I conclude that the size effect is likely to be stronger than previously thought. It may seem insignificant in recent years (see Schwert, 2003) just because it runs counter to the idiosyncratic volatility discount and both idiosyncratic volatility and its effect on returns have also recently increased (Campbell et al., 2001, and AHXZ, Table XI).

In Barinov (2007) I explore the link between the size effect and the idiosyncratic volatility discount further and find that the change in the slope is no coincidence. Barinov (2007) shows that if one sorts on the size variable orthogonalized to idiosyncratic volatility, the size effect in returns doubles and restores its significance in all time periods.

1.5 Time-Series Tests

1.5.1 Is Aggregate Volatility Risk Priced?

Changes in aggregate volatility provide information about future investment opportunities and future consumption. In Campbell (1993), an increase in aggregate volatility implies that in the next period risks will be higher and consumption will be lower. Consumers, who wish to smoothen consumption, have to save and cut current consumption if aggregate volatility goes up. Chen (2002) also notes that higher current aggregate volatility means higher aggregate volatility in the future. Therefore, consumers will build up precautionary savings and cut current consumption in response to volatility increases. Both Campbell (1993) and Chen (2002) predict that the most negatively correlated with changes in aggregate volatility stocks earn a risk premium. These stocks are risky because their value drops when consumption has to be cut to increase savings.

Ang, Hodrick, Xing, and Zhang (2006) (henceforth - AHXZ) show that stocks with positive return sensitivity to the innovations in the VIX index indeed earn about 1% per month less than stocks with negative sensitivity. The VIX index measures the implied volatility of the S&P100 options and behaves like a random walk. The change in VIX is therefore a good proxy for the innovation in expected aggregate volatility.

In this subsection I extend the findings of AHXZ by showing that aggregate volatility risk is priced for several portfolio sets and that the ICAPM with the aggregate volatility risk factor performs at least as well as the Fama-French model.

I measure return sensitivity to the aggregate volatility movements by regressing firm daily excess returns on excess market returns and the change in the VIX index, as AHXZ do. I run these regressions separately for each firm-month, and require at least 15 non-missing observations for each firm-month. The sample period is from February 1986 to December 2006, because the CBOE data on VIX start in January 1986, and I lag the return sensitivities to VIX changes by one month to form the BVIX factor.

In each month, I sort firms by their VIX sensitivity in the previous month and form the BVIX factor portfolio. It is long in the lowest sensitivity quintile and short in the highest sensitivity quintile. The BVIX factor is the factor I use to augment the CAPM to explain the three idiosyncratic volatility effects. AHXZ employ a more sophisticated procedure of forming the factor-mimicking portfolio (FVIX), which tracks the changes in VIX. I choose a simpler procedure to form the BVIX factor mainly because of estimation error concerns.

In Panel A of Table 4 I verify that sorting stocks on return sensitivity to the VIX changes creates a spread in returns unrelated to other priced factors. Panel A shows that the return differential is between 86 to 98 bp per month, depending on the risk factors I control for. It is slightly lower than what AHXZ (2006) document in 1986-2000.

In Panel B of Table 4, I use the Gibbons, Ross, and Shanken (1989) (hereafter - GRS) test statistic to compare the performance of the CAPM, the Fama-French model, and the ICAPM with the BVIX factor. The GRS statistic tests whether the alphas of all portfolios in a portfolio set are jointly equal to zero, and whether the BVIX betas of all portfolios are jointly equal to zero. The GRS statistic gives more weight to more precise alpha estimates, which usually come from low volatility stocks. Because BVIX should explain the alphas of high volatility firms, the GRS statistic estimates the usefulness of BVIX quite conservatively. The tests in Panel B use equal-weighted returns to the portfolios sets. Using value-weighted returns instead does not change the conclusions.

Panel B brings me to three main conclusions. First, the BVIX betas are highly jointly significant for all portfolio sets. Second, adding the BVIX factor to the CAPM always significantly improves the GRS statistic for alphas, though it still remains significant. The improvement of the GRS statistic is about 17% for the 25 idiosyncratic volatility - market-to-book portfolios and about 4% and 6% for the 25 size - market-to-book portfolios and the 48 industry portfolios. Third, for the 25 idiosyncratic volatility - market-to-book portfolios and the 48 industry portfolios the ICAPM with BVIX performs better in terms of alphas

than the Fama-French model.

In the second chapter I take a more detailed study of the BVIX factor pricing ability. I find that the improvement over the CAPM in the 25 size - market-to-book portfolios comes from the BVIX factor ability to explain the abnormally low returns to the smallest growth firms and, consequentially, the puzzling negative size effect in the extreme growth quintile. The respective alphas are reduced by more than a half and become insignificant. I also show that the BVIX factor provides an explanation of the new issues puzzle. The ICAPM with BVIX reduces the alphas of the IPO and SEO portfolios by about 45% and makes them insignificant. The BVIX factor is also successful in explaining the abysmal performance of new issues performed by small firms and growth firms, and its difference with the performance of the new issues performed by large firms and value firms. Coupled with the evidence in Table 5, it suggests that the BVIX factor is not an *ad hoc* patch on the CAPM. Rather, it is a priced factor, helpful in resolving many puzzles the existing asset-pricing models cannot fully address and significant in explaining returns to a wide variety of portfolios.

1.5.2 The Three Idiosyncratic Volatility Effects and Aggregate Volatility Risk

My model establishes an economy-wide idiosyncratic volatility hedging channel. As the economy slides into recession and expected aggregate volatility increases, the corresponding increase in idiosyncratic volatility mutes the effect of the bad news on growth options for two reasons. First, higher idiosyncratic volatility in my model means lower risk of growth options. Hence, the presence of idiosyncratic volatility makes smaller any increase in the risk premium of growth options caused by the recession, and also makes smaller any corresponding drop in their value. Second, higher idiosyncratic volatility makes growth options more valuable, which also mutes any drop in their value the recession may cause.

In Propositions 3 and 4, I show that both mechanisms behind the idiosyncratic volatility channel are stronger for high volatility, growth, and especially high volatility growth firms. It makes these three types of firms good hedges against aggregate volatility risk, as their returns covary least negatively with the changes in aggregate volatility. Therefore, aggregate volatility risk should explain the three idiosyncratic volatility effects: the idiosyncratic volatility discount, the stronger value effect for high volatility firms, and the stronger idiosyncratic volatility discount for growth firms.

To get the idea of how helpful the BVIX factor may be in explaining the idiosyncratic volatility effect, I report its betas from the ICAPM with BVIX run at monthly frequency for each of the 25 idiosyncratic volatility - market-to-book portfolios. A negative BVIX beta implies that the portfolio returns are positive when the stock with the most negative correlation with aggregate volatility lose value. Hence, portfolios with negative BVIX betas are hedges against aggregate volatility risk.

Table 5 shows that the BVIX betas are closely aligned with the Fama-French alphas in Table 2. High idiosyncratic volatility firms have negative BVIX betas that are significantly lower than the BVIX betas of low volatility firms. In all market-to-book quintiles the BVIX betas decrease almost monotonically as idiosyncratic volatility increases. Growth firms also have significantly lower BVIX betas than value firms. With few exceptions, in all volatility quintiles the BVIX betas decrease monotonically with market-to-book. It suggests that both the idiosyncratic volatility discount and the value premium can be at least partly explained by sensitivity to aggregate volatility.

Most importantly, the BVIX betas spread between high and low volatility firms increases with market-to-book, and the BVIX betas spread between value and growth firms increases in idiosyncratic volatility. Panel A of Table 4 estimates the factor premium earned by BVIX at 0.9% per month, which makes the spread in the BVIX betas enough to explain from 50% to 75% of the idiosyncratic volatility discount. In Panel A of Table 5 that uses value-weighted returns the BVIX betas of low and high volatility firms differ by only 0.199 (t-statistic 1.99) in the value quintile. The differential increases to 0.604 (t-statistic 3.57) in the growth quintile. The difference is highly significant with t-statistic 3.37. Similarly, the BVIX betas spread between value and growth is zero in the bottom three idiosyncratic volatility quintiles, but it increases to 0.260 (t-statistic 2.32) and 0.382 (t-statistic 2.75) in the fourth and the fifth volatility quintile. I also observe a highly negative BVIX beta of -0.395, t-statistic -2.94, for the highest volatility growth portfolio, which shows it is a very good hedge against aggregate volatility increases.

The results in Panel B that looks at equal-weighted returns are, if anything, stronger. The BVIX betas spread between low and high volatility in the growth quintile increases to 0.702, t-statistic 2.67, and is 0.526, t-statistic 3.57, higher than the similar spread in the value quintile. The BVIX betas spread between value and growth is also slightly higher at 0.412, t-statistic 4.01, and the BVIX beta of the highest volatility growth portfolio

becomes as low as -0.527, t-statistic -2.56.

The conclusion from Table 5 is that, consistent with my model, high volatility firms, growth firms, and especially high volatility growth firms hedge against aggregate volatility risk. Their prices tend to go up when the prices of the firms with the most negative correlation with aggregate volatility go down. Their BVIX betas are significantly lower than the BVIX betas of low volatility, value and low volatility value firms, which can explain a large fraction of the three idiosyncratic volatility effects.

1.5.3 The Three Idiosyncratic Volatility Effects, the Conditional CAPM, and the Business Cycle

The return sensitivity to changes in the BVIX index is not the most common measure of firm exposure to economy-wide shocks. In this section, I use a more popular framework of the conditional CAPM to corroborate the findings from the previous subsection. In my tests I rely on Proposition 3 that predicts that the risk exposure of high idiosyncratic volatility, growth, and especially high volatility growth firms tends to decrease in recessions, when risk is higher.

I use four arbitrage portfolios that measure the three idiosyncratic volatility effects. The IVol portfolio captures the idiosyncratic volatility discount. It goes long in low volatility firms and short in high volatility firms. The IVolh portfolio does the same for growth firms only to capture the stronger idiosyncratic volatility discount in the growth quintile. The HMLh (HMLl) portfolios look at the value effect for high (low) volatility firms. The HMLl portfolio is not particularly challenging for the unconditional models and is used only for comparison with HMLh. The IVol55 portfolio is long in the highest volatility growth firms and short in the one-month Treasury bill.

Proposition 3 implies that when the expected market risk premium is high, the market beta of the first four (last) portfolios is higher (lower) than in good states of the world. In what follows, I assume that the expected market risk premium and the conditional beta are linear functions of the four commonly used business cycle variables - dividend yield, default spread, one month Treasury bill rate, and term spread. I define the bad state of the world, or recession, as the months when the expected market risk premium is higher than its in-sample mean.

In Table 6, I look at the average market betas across the states of the world for the five

arbitrage portfolios I study. The expected market return is estimated as the fitted part of the regression

$$MKT_t = \gamma_0 + \gamma_1 \cdot DIV_{t-1} + \gamma_2 \cdot DEF_{t-1} + \gamma_3 \cdot TB_{t-1} + \gamma_4 \cdot TERM_{t-1} + \epsilon_t \quad (22)$$

To estimate the conditional CAPM beta, I run the regression

$$Ret_{it} = \alpha_i + (\beta_{0i} + \beta_{1i} \cdot DIV_{t-1} + \beta_{2i} \cdot DEF_{t-1} + \beta_{3i} \cdot TB_{t-1} + \beta_{4i} \cdot TERM_{t-1}) \cdot MKT_t + \epsilon_{it} \quad (23)$$

and define the conditional beta as

$$\beta_i = \beta_{0i} + \beta_{1i} \cdot DIV_{t-1} + \beta_{2i} \cdot DEF_{t-1} + \beta_{3i} \cdot TB_{t-1} + \beta_{4i} \cdot TERM_{t-1} \quad (24)$$

The left part of Table 6 looks at value-weighted returns and shows very strong evidence in favor of my model. For value-weighted returns I find that for the IVol and IVolh the conditional CAPM betas are by 0.202 and 0.288 higher in recessions than in expansions (standard errors 0.051 and 0.061, respectively). It means that exploiting the idiosyncratic volatility discount implies high exposure to business cycle risk. Also, the IVol55 portfolio turns out to be a good hedge against adverse business cycle movements, as its beta is by 0.177 (standard error 0.035) lower in recessions than in expansions. The right part of Table 6, which uses equal-weighted returns, shows very similar results.

I also find, consistent with Proposition 3, that the betas of the HMLl portfolio do not show reliable dependence on business cycle. The HMLl beta differential between recessions and expansions is small and its sign depends on whether I use value-weighted or equal-weighted returns. On the other hand, the CAPM beta of HMLh portfolio is by 0.286 higher in recessions (standard error 0.035) for value-weighted returns and by 0.223 higher in recessions (standard error 0.036) for equal-weighted returns. The difference in the conditional beta sensitivity to business cycle between HMLl and HMLh reinforces the conclusion from Table 3 and Table 5 that the value effect is at least partly driven by the interaction of growth options and volatility.

Petkova and Zhang (2005) perform a similar analysis for the HML portfolio. In a time frame very similar to mine they find that the conditional CAPM beta of the HML portfolio is only by 0.05 higher in recessions than in expansions, which is two to six times smaller than the spread in conditional betas I find for my portfolios.

A natural question to ask is whether the variation in the conditional betas is likely to be enough to explain the idiosyncratic volatility effects. In unreported results, I find

that the expected and realized market risk premium is higher in recessions by about 1% per month. Coupled with the variation in betas, for example, of the IVol portfolio, the conditional CAPM is likely to explain only 20 bp of the 60 bp idiosyncratic volatility discount, i.e. only a third of the anomaly. I hypothesize, and show in the next subsection, that the failure of the conditional CAPM occurs because it ignores the hedging demands captured by the ICAPM.

1.5.4 Explaining the Three Idiosyncratic Volatility Effects

In Table 7, I test the ability of a variety of asset-pricing models to explain the idiosyncratic volatility effects represented by the returns to the four portfolios - IVol, IVolh, HMLh, and IVol55 - described at the start of the previous subsection. The sample period is determined by the availability of the VIX index and goes from February 1986 to December 2006.

In the first two columns I present the alphas from the unconditional CAPM and the unconditional Fama-French model. The unconditional CAPM turns out to be incapable of explaining either the value-weighted or the equal-weighted returns to any of the portfolios except for the equal-weighted IVol portfolio, which has the insignificant equal-weighted alpha. The magnitude of the CAPM alphas is about 1% per month. The Fama-French model can handle the equal-weighted IVolh portfolio and the value-weighted IVol55 in addition to the equal-weighted IVol portfolio, but desperately fails on the rest. The significant Fama-French alphas are around 0.6% per month.

In the next pair of columns, I estimate the ICAPM with the BVIX factor and find that it perfectly explains the returns to all portfolios except for HMLh. For example, the IVolh portfolio measures the idiosyncratic volatility discount in the extreme growth quintile and possesses the value-weighted CAPM and Fama-French alphas of 114 bp per month (t-statistic 3.03) and 67 bp per month (t-statistic 2.08), respectively. Adding the BVIX factor to the CAPM cuts the alpha to 54 bp per month, t-statistic 1.38.

The explanatory power of BVIX is also visible in the fourth column, which reports the BVIX betas of the four portfolios. The BVIX betas vary from 0.4 to 0.7 and are highly statistically significant. Trying to exploit the three idiosyncratic volatility effects exposes the investor to extremely high levels of aggregate volatility risk. The returns to the IVol, IVolh, and HMLh portfolios tend to be very low when aggregate volatility is high and consumption is low.

The fact that the BVIX does not completely explain the returns to the HMLh portfolio is not surprising if one thinks there is something to the value effect except for the interaction between growth options and idiosyncratic volatility. What my model predicts is that BVIX should be useful in explaining the returns to HMLh, and the highly significant BVIX betas of HMLh portfolio suggest it is useful. The reduction in the HMLh alpha brought about by adding BVIX to the CAPM is 40 bp, less than what the Fama-French model is able to achieve, but still quite sizeable.

As I argued in Section 2.2, there are several reasons why BVIX, the aggregate volatility risk factor, should explain the three idiosyncratic volatility effects. In the conditional CAPM framework, which assumes that investors do not care about intertemporal substitution, the BVIX factor should be regarded as a proxy for what Jagannathan and Wang (1996) call the beta instability risk. Essentially, the conditional CAPM says that the BVIX factor is a quasi-factor that should eliminate the negative bias in the unconditional alphas, created by the negative correlation between the market beta and the market risk premium. In the conditional CAPM, the BVIX factor can capture only a part of the beta instability risk, because there are other conditioning variables, beyond aggregate volatility, that are related both to idiosyncratic volatility and expected market risk premium.

In the ICAPM, the idiosyncratic volatility hedging channel has more impact, which includes the role it plays in the conditional CAPM. The ICAPM embraces the beta instability risk. It also points out that the smaller increase of risk premium in recession means the smaller decrease in current stock prices as the news about the recession arrive. The smaller decrease in price yields additional consumption when it is most valuable because both the future investment opportunities become worse (Campbell, 1993) and the higher future volatility calls for more precautionary savings (Chen, 2002).

Also, growth options hedge against the above negative consequences of aggregate volatility because their value increases as volatility increases. This effect is naturally stronger for growth firms and high volatility firms. This is another reason why growth firms and high volatility firms provide additional consumption when it is most needed and why they are good hedges against aggregate volatility risk.

In sum, the explanatory power of the conditional CAPM and the ICAPM should overlap, but none of them should subsume the other. The BVIX factor can be an imperfect proxy for the beta instability risk, but it is also capable of capturing other dimensions of

risk that are absent in the conditional CAPM. The ability to capture other dimensions of risk is the reason why I expect the ICAPM with BVIX to outperform the conditional CAPM in explaining the three idiosyncratic volatility effects.

The fifth column of Table 7 reports the alphas of the conditional CAPM in Section 5.3, equation (23). I assume that the conditional market beta is a linear function of the dividend yield, the default spread, the one-month Treasury bill rate, and the term spread. The alphas are significantly smaller than the unconditional CAPM alphas in the first column, usually by about 25%, or by 20-35 bp, quite close to what the back-of-envelope calculation in the end of Section 5.3 predicts. However, the conditional CAPM alphas are generally significant and considerably lag behind the Fama-French and ICAPM alphas.

In columns six and seven I look at the conditional ICAPM, where only the market beta is conditioned on the four business cycle variables. The point of this exercise is to evaluate the overlap between the BVIX factor and the conditioning variables. As I argued above, I expect some overlap, and some unique risk in both the BVIX factor and the conditioning variables, with BVIX picking up more significant risks.

In column six I look at the alphas and see that they are uniformly reduced by 10-15 bp compared to the ICAPM alphas in the third column. Most of them are reduced from insignificant values and the significant ones do not become insignificant. The results suggest that the BVIX factor captures the majority of the beta instability risk, but some of it is still captured by the conditioning variables only. The overlap between the conditioning variables and BVIX is further confirmed by column seven, which reports the BVIX betas in the conditional ICAPM. The BVIX betas uniformly decrease by about 0.1 and even become marginally significant in equal-weighted returns. However, most of the betas remain large and statistically significant, which confirms that there are important risks captured by the BVIX factor, but not by the conditioning variables.

1.6 Conclusion

My paper presents a real options model, which explains the idiosyncratic volatility discount and the stronger value effect for high volatility firms. The basic intuition driving these two results is that high idiosyncratic volatility decreases the risk of growth options by making them less sensitive to the changes in the underlying asset value. Because in my model the

pricing effects of idiosyncratic volatility work through growth options, it generates a new empirical prediction that the idiosyncratic volatility discount is stronger for growth firms and absent for value firms.

My model predicts that aggregate volatility risk explains the idiosyncratic volatility discount. Aggregate volatility risk should also explain why idiosyncratic volatility discount is stronger for growth firms and why the value effect is stronger for high volatility firms. The reason is the idiosyncratic volatility hedging channel. An increase in aggregate volatility signals a recession, when expected risk premium is high. However, higher aggregate volatility also means higher idiosyncratic volatility, which diminishes the increase in the risk premium for growth options. Higher idiosyncratic volatility also makes growth options more valuable. Both effects mute the drop in the firm value in recessions. The idiosyncratic volatility hedging channel is the strongest for high volatility, growth, and high volatility growth firms. The returns to these firms covary least negatively with changes in expected aggregate volatility. So, these firms have the lowest aggregate volatility risk.

The cross-sectional predictions of my model find strong support in the data. I find in portfolio sorts that the idiosyncratic volatility discount is much stronger for growth firms and absent for value firms. I confirm it by running Fama-MacBeth regressions of returns on firm characteristics. Adding the product of volatility and market-to-book changes the signs of idiosyncratic volatility and market-to-book. It suggests that the interaction between idiosyncratic volatility and growth options predicted by my model can potentially explain the idiosyncratic volatility discount and the value effect.

Controlling for idiosyncratic volatility greatly increases the magnitude and significance of the size effect. The size effect predicts that small firms, which are also high volatility firms, earn high returns. The idiosyncratic volatility discount predicts just the opposite. My results suggest that the size effect seems weak because of this conflict, not because size per se is not important.

In time-series tests, I introduce the aggregate volatility risk factor - the BVIX factor. It is similar to the one used by Ang, Hodrick, Xing, and Zhang (2006). The BVIX factor is an arbitrage portfolio long in the firms with the most negative and short in the firms with the most positive return sensitivity to aggregate volatility increases. I show that BVIX earns a large premium controlling for the three Fama-French risk factors and is priced for different portfolio sets.

I show that high volatility, growth, and especially high volatility growth firms have large and negative BVIX betas. It means that they provide a hedge against the aggregate volatility risk, as predicted by my model. I also show that these three types of firms have significantly lower conditional CAPM betas in recessions than in expansions. The conditional betas provide additional evidence that high volatility, growth, and high volatility growth firms are a hedge against adverse economy-wide shocks. Their risk exposure turns out to be the lowest when the risk is the highest.

Augmenting the CAPM by the BVIX factor perfectly explains the idiosyncratic volatility discount and its dependence on market-to-book, as well as the abysmal returns to the highest volatility growth firms. The Intertemporal CAPM with BVIX also reduces by about a third the abnormally large value effect for high volatility firms.

2 Aggregate Volatility Risk: Explaining the Small Growth Anomaly and the New Issues Puzzle

2.1 Introduction

In a recent paper, Ang, Hodrick, Xing, and Zhang (2006) find a large and significant return differential between the firms with the most and the least negative return sensitivity to aggregate volatility increases. They proceed to form an aggregate volatility risk factor and show that it is priced in cross-section.

The aggregate volatility risk factor leans on the models in Campbell (1993) and Chen (2002). Campbell (1993) shows that higher expected volatility means higher expected returns and lower current prices. Hence, the assets that react less negatively to aggregate volatility increases provide an important hedge against adverse changes in future investment opportunities. Chen (2002) shows that higher expected volatility means higher need for precautionary savings and, therefore, lower current consumption. In his model, the assets with less negative reaction to aggregate volatility increases are valuable, because their prices do not drop when consumption drops to build up precautionary savings.

In the first chapter, I develop a real options model predicting that high idiosyncratic volatility, growth, and high volatility growth firms hedge against aggregate volatility risk. In the empirical part of the first chapter I successfully use the aggregate volatility risk factor (henceforth, the BVIX factor) to explain the idiosyncratic volatility discount, the stronger value effect for high volatility firms, the stronger idiosyncratic volatility discount for growth firms, and abysmally low returns to high volatility growth firms.

Brav, Geczy, and Gompers (2000) show that the small growth anomaly (Fama and French, 1993) and the new issues puzzle (Loughran and Ritter, 1995) are essentially one anomaly, not two. They argue that if there is a risk-based explanation of one puzzle, it also should resolve the other. The main contribution of my paper is locating one risk factor that explains both anomalies - the aggregate volatility risk factor, or the BVIX factor. BVIX is also helpful in explaining why the new issues puzzle is stronger for small firms and growth firms and why we observe the cumulative issuance puzzle (see Daniel and Titman, 2006). Essentially, I propose a firm-type story: new issues and heavily issuing firms seem to underperform because they are of the type (small growth, or better, high

volatility growth) that underperforms relative to the existing asset-pricing models.

In the model in the first chapter, idiosyncratic volatility affects expected returns via growth options. The beta of growth options is, by Ito's lemma, the product of the underlying asset beta and the option value elasticity with respect to the underlying asset value. While changes in the idiosyncratic volatility of the underlying asset do not influence its beta, they do make the elasticity and the growth options beta smaller. Naturally, because idiosyncratic volatility affects returns via growth options, my model predicts stronger idiosyncratic volatility discount for growth firms.

The lower elasticity of options on high volatility assets is intuitive. Consider, for example, two at-the-money options with the same maturity (say, one year) written on two underlying assets, one with 50% annual volatility and the other with 5% annual volatility. A 10% drop in the value of the not volatile underlying asset means that the option on it will be out of the money at the expiration with 98% probability. The same 10% drop in the value of the volatile underlying asset will not imply much about option value at the expiration. It will not therefore influence the option price as much as it does for the option on the not volatile asset. That is, the value of the option will be more elastic if the underlying asset is less volatile.

When I take this reasoning to time-series, I discover that high volatility firms offer a hedge against volatility increases in bad times. Their betas tend to fall when aggregate volatility and expected risk premium increase. Moreover, higher idiosyncratic volatility strengthens the positive reaction of growth options value to volatility increases. Therefore, the returns to high volatility firms exhibit less negative reaction to aggregate volatility increases. This effect is stronger for the firms with many growth options, leading to the conclusion that the best hedge against adverse volatility shocks is to hold high volatility growth stocks.

Small stocks are often high idiosyncratic volatility stocks and share many of their characteristics, such as high uncertainty about the stock value and opaque information environment. Moreover, small stocks tend to earn low returns if they are also growth stocks, even though on average small caps earn higher returns than large caps. Therefore, the BVIX factor that has already explained the abysmally low returns to high volatility growth stocks is a natural potential explanation for the small growth anomaly.

The same is true for IPOs, which tend to be small growth (see Brav, Geczy, and Gom-

pers, 2000) and highly volatile (see Fama and French, 2004) stocks with high uncertainty about their prospects. To a smaller, but still significant extent, the same characteristics apply to SEOs (see Brav, Geczy, and Gompers, 2000) and, as I show, to the firms that create the cumulative issuance puzzle discovered by Daniel and Titman (2006). Hence, the underperformance of new issues and firms with high cumulative issuance is also one of the implications the my model and should be explained by the BVIX factor.

The empirical results are supportive of my hypotheses. I find that the ICAPM with the BVIX factor reduces by more than a half the anomalous negative alphas to the two smallest size portfolios in the lowest book-to-market quintile and pushes the alphas well below the conventional significance levels. The BVIX factor betas for the two anomalous portfolios are large and significantly negative.

The BVIX factor also explains about 45% of the new issues puzzle and the cumulative issuance puzzle and makes the alphas of the respective portfolios statistically insignificant. Large and significantly negative BVIX betas of new issues and heavily issuing firms lend further support to the risk-based explanation of the new issues puzzle.

Lyandres, Sun, and Zhang (2007) propose another explanation of the new issues puzzle. Leaning on the Q-theory, they argue that the firms issuing equity do that because they are taking advantage of the low-risk projects they have. Lyandres, Sun, and Zhang propose the use of the investment factor, which is the return differential between low investment and high investment firms. If the new issues are similar to other high investment and low return firms, then the new issues underperformance is not anomalous. Lyandres, Sun, and Zhang find that the investment factor explains about 80% of new issues underperformance and about 40% of the cumulative issuance puzzle in their sample.

The aggregate volatility risk explanation and the investment explanation of the new issues puzzle are not mutually exclusive. I find that they explain the same amount of the IPO and SEO underperformance. When the investment factor and the BVIX factor are added to the CAPM together, they hardly reduce the explanatory power of each other. The alpha of the new issues portfolios is reduced to exactly zero in the ICAPM with the BVIX factor and the investment factor. In event time, I find that the BVIX betas are almost flat across the event period, confirming that my story for new issues is a firm-type story, and the investment betas capture some of the risk shift, which is necessary to explain why the new issues underperformance is most severe 6 to 24 months after the issue.

The model in the first chapter suggests taking the analysis one step further. It implies that small growth firms are a hedge against aggregate volatility risk, and so are the new issues and high cumulative issuance firms, because they are also small growth firms. If it is true, then the new issues puzzle and the cumulative issuance puzzle should be strong for small and growth firms and virtually non-existent for large and value firms.

I test this prediction and find that the new issues puzzle is indeed larger for small firms and growth firms, and the BVIX factor explains this pattern. The investment factor cannot capture the cross-section of the new issues puzzle, producing the same investment betas for new issues in all size and market-to-book portfolios. Looking at the cross-section of the cumulative issuance puzzle brings me to similar conclusions, with the strong result that the investment factor explains the puzzle only for large firms.

An interesting by-product of my study is the discovery of the January 2001 problem in equal-weighted returns. In January 2001, the smallest growth portfolio witnesses a huge windfall of 55%, followed by the windfall of 36% accruing to the second smallest growth portfolio and the smallest firms in the second lowest book-to-market quintile. Similar extreme gains accrue to the new issues portfolios - the portfolios of recent IPOs (SEOs) make 39% (24%) in January 2001. These outliers are powerful enough to materially reduce the size and the significance of the small growth puzzle in the last 21 years of data. I also show that the extreme success of the investment factor in Lyandres, Sun, and Zhang (2007) is driven by the January 2001 problem. With January 2001 in sample, the investment factor explains about 80% of the new issues underperformance. If I drop this single data point, the investment factor explains only 50% of the underperformance. I conclude that the January 2001 problem is important enough to be kept in mind in any analysis that includes equal-weighted returns to small growth firms.

The rest of the chapter proceeds as follows. In Section 8, I describe the data. In Section 9, I test if the BVIX factor is priced in time-series for different portfolio sets and use the BVIX factor to explain the small growth anomaly. In Section 10, I look at the new issues puzzle, the relation between the BVIX factor and the investment factor. Section 10 also studies new issues puzzle in the cross-section and in the event time. In Section 11, I examine the cumulative issuance puzzle, its relation to the small growth anomaly, and its dependence on size and market-to-book. In Section 12, I conclude and discuss directions for future research.

2.2 Data

The data used in the paper are from CBOE, Compustat, CRSP, SDC Platinum database, and Kenneth French's website. The expected aggregate volatility is proxied by the old VIX index calculated by CBOE, which measures the implied volatility of one-month options on S&P 100⁵. I get the values of the VIX index from CBOE data on WRDS. Using the old version of the VIX gives me a longer data series compared to newer CBOE indices.

I measure the return sensitivity to changes in the VIX by running each firm-month the regressions of the daily excess returns to the stock on the daily excess returns to the market and the VIX change in this day. The daily stock returns are from CRSP, and the daily excess market return and the daily risk free rate come from Kenneth French's website. I require at least 15 non-missing returns in a firm-month for the estimation.

The BVIX factor is defined as the difference of value-weighted returns to the most negative and most positive VIX sensitivity quintile. The quintiles are based on the previous month sensitivity and are held for one month. Ang, Hodrick, Xing, and Zhang (2006) use FVIX factor instead, which is the factor-mimicking portfolio tracking the VIX index. I use a simpler procedure to form my aggregate volatility risk factor because of estimation error concerns. The sample period of my study is from February 1986 to December 2006, because the VIX index starts in January 1986, and I lag the VIX sensitivity by one month to form the BVIX factor.

In Section 9, I use three portfolio sets to test if the BVIX factor is priced. Two of them - the 25 size - book-to-market portfolios (Fama and French, 1993) and the 48 industry portfolios (Fama and French, 1997) - come from Kenneth French's website. The third portfolio set is the 25 idiosyncratic volatility - market-to-book portfolios from the first chapter. The idiosyncratic volatility is defined as the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily data for each firm-month with at least 15 non-missing observations. The market-to-book is from Compustat and is defined as the sum of item #60 and item #74 over the product of item #25 and item #199. The firms are sorted in idiosyncratic volatility and market-to-book quintiles independently, using NYSE breakpoints. The idiosyncratic volatility portfolios use the previous month idiosyncratic volatility and are rebalanced each month. The market-to-book quintiles use

⁵For a detailed description of VIX, see Whaley (2000).

the market-to-book lagged at least 6 months and are rebalanced annually. The daily and the monthly Fama-French factors are from Kenneth French's website ⁶.

In Section 10, I use the SDC Platinum database to extract the dates of new issues and the identities of the issuing firms. I match the new issues with the CRSP returns data by the six-digit CUSIP, requiring at least one valid return observation in the three years after the issue. My IPO and SEO portfolios are rebalanced monthly and include the IPOs and SEOs performed from 2 to 37 months ago. The first month is excluded because of the well-known IPO underpricing and the price support of the underwriters in the month after the issue. The results are robust to keeping the first month in the sample. I include only the IPOs and SEOs listed on NYSE/AMEX/NASDAQ after the issue (the `exchcd` listing indicator from CRSP events file is used). I keep utilities in my sample, as well as mixed SEOs, but discard SEOs with no new shares issued and units issues (both IPOs and SEOs). Excluding financials and mixed SEOs, or including units issues does not change my results. My sample includes 5969 IPOs and 6974 SEOs performed between December 1982 and October 2006 (new issues in 1983 enter the new issues portfolio in 1986 as two to three year old issues). When I look at the new issues puzzle in different size and market-to-book portfolios, I measure size and market-to-book using the after-issue market capitalization and total common equity values from SDC.

The investment factor is from Lyandres, Sun, and Zhang (2007)⁷. The investment-to-assets ratio is the sum of the annual changes of gross PPE (Compustat item #7) and inventories (item #3) divided by the lagged value of book assets (item #6). Each year firms are sorted independently on market-to-book, market value, and the investment-to-assets ratio and put into three groups on each measure (top 30%, middle 40%, and bottom 30%). The investment factor is the value-weighted return differential between bottom and top investment-to-assets firms, averaged across all size and market-to-book groups.

In Section 11, I follow the definition of the cumulative issuance variable in Daniel and Titman (2006). The cumulative issuance is the growth of the market value unexplained by returns to the pre-existing assets and is measured as the log market value growth minus the log cumulative holding-period returns in the past five years.

⁶<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>

⁷I thank Le Sun for making available the updated values of the investment factor on his home page at <http://www.lesun.com>.

2.3 Aggregate Volatility Risk and the Small Growth Anomaly

The smallest growth portfolio is widely recognized to be the worst failure of the Fama-French model. The Fama-French alpha of this portfolio in different periods is more than -50 bp per month and is much less than the alpha of the largest growth portfolio, which should earn the lowest return in the Fama-French world. The portfolios close to the smallest growth portfolio also tend to have abnormally low alphas. The underperformance of the small growth firms is likely to be one of the drivers of other important anomalies, such as the new issues underperformance, higher value effect for the smallest firms, and the negative size effect for growth firms.

The model I develop in the first chapter produces a mechanism that is likely to explain the small growth anomaly. In the model, higher idiosyncratic volatility makes growth options less sensitive to the value of the underlying asset. The sensitivity decreases because the more volatile the underlying asset is, the less informative its current value is about the option value at the expiration date. By Ito's lemma, the beta of growth options is the product of the underlying asset beta and the option value elasticity with respect to the underlying asset value. The decrease in sensitivity implies the decrease in the growth options beta, because idiosyncratic volatility does not change the underlying asset beta. Because in the model idiosyncratic volatility affects expected returns via growth options, at the firm-level its effect on expected returns will be stronger if the firm has more growth options.

In recessions, both aggregate volatility and idiosyncratic volatility increase⁸. The increase in idiosyncratic volatility makes growth options betas smaller and mutes the increase in their risk premiums in recessions. Hence, the value of growth options drops less when the bad news arrives. In my model, this effect is stronger for high idiosyncratic volatility firms and growth firms.

Growth options also hedge against adverse business-cycle shocks through one more hedging channel. As the economy enters the recession and volatility increases, the value of growth options, like the value of any option, tends to increase with volatility. This hedging channel is naturally stronger for growth firms, and, as the model in the first chapter can show, for high volatility firms.

⁸See, e.g., Campbell, Lettau, Malkiel, and Xu, 2001

In sum, the model in the first chapter shows that returns to high volatility growth stocks should covary least negatively with changes in expected aggregate volatility. It means that high volatility growth firms are the best hedges against aggregate volatility risk.

The first chapter shows empirically that the abnormally low observed returns to high volatility growth firms are successfully explained by the ICAPM with the BVIX factor. Since small growth firms usually have high idiosyncratic volatility and share many characteristics of high volatility growth firms, the BVIX factor is a natural candidate for the explanation of the small growth anomaly and related puzzles.

Before I start the empirical tests, I want to point out one unusual and influential observation in my sample period. In a single month of January 2001, the smallest growth portfolio witnessed a windfall of 55.6%. A similar windfall accrued to the second smallest growth portfolio - it made 36.2% in the same month, and the smallest second lowest book-to-market portfolio made 36.4%. These returns to the usually worst-performing portfolios are the largest not only in the Compustat era, but also in the whole observation history starting with 1940.

To put the returns in another prospective, the two smallest growth portfolios normally earn only 9% per year in the Compustat era and 4% and 6% per year in my sample period. While it is true that the conventional January effect is very strong in the two smallest growth portfolios and the vast majority of their annual return is realized in January, January 2001 still looks as a clear outlier even among other Januaries. The second maximum January return to the smallest growth portfolios is about two times smaller than the January 2001 return.

Because the January 2001 outlier seems powerful enough to bias my estimates and to reduce the power of my tests of the small growth anomaly and its explanation, I perform my analysis both with keeping January 2001 observations in my sample and excluding them. I also look both at equal-weighted and value-weighted returns, because the January 2001 problem is weaker in value-weighted returns.

In Table 8, I look at the returns to the size quintiles in the lowest book-to-market quintile. Simply comparing the CAPM and the Fama-French equal-weighted alphas to the smallest growth portfolio with and without January 2001 (Panel B and Panel A, respectively), we can notice that including January 2001 in the sample reduces the alphas

by about 20 bp per month (20% and 30% of their value in the CAPM and the Fama-French model) and makes them marginally insignificant. The second smallest growth portfolio gets a smaller hit - its alphas are reduced by about 12 bp per month (15% and 25% of their value) and remain statistically significant.

The value-weighted returns confirm that the weakening of the small growth anomaly because of the January 2001 outlier is spurious rather than real. The January 2001 problem is much weaker in value-weighted returns, and the alphas of the two smallest growth portfolios decrease only by about 5 bp and remain highly significant if I keep January 2001 in the sample. So, I choose to study first the small growth anomaly with January 2001 excluded.

Panel A of Table 8 shows that the smallest and the second smallest growth portfolios earn large and significant CAPM alphas. The equal-weighted alphas of these portfolios are -86 bp and -75 bp, respectively (t-statistics -2.08 and -3.19). I also observe the negative size effect of -79 bp per month (t-statistic -1.81) in the extreme growth quintile. The value-weighted CAPM alphas of the two smallest growth portfolios are -1% and -0.6% per month (t-statistics -2.93 and -2.52), and the negative size effect is estimated at -1% per month, t-statistic -2.64. In the first chapter I find that the idiosyncratic volatility discount is stronger in value-weighted returns. If the idiosyncratic volatility discount is behind the small growth anomaly, it is natural that the small growth anomaly and the negative size effect for growth firms are stronger in value-weighted returns.

The Fama-French model cannot explain the small growth anomaly and the negative size effect for growth firms either. The estimate of the negative size effect barely changes after I control for SMB and HML and even gains significance. The alphas of the smallest growth portfolios are reduced by 25 to 50 percent, but remain highly significant.

When I estimate the ICAPM with the BVIX factor, which should be the cure for the small growth anomaly, I see that the small growth anomaly is perfectly explained. The equal-weighted and value-weighted alphas of the smallest growth portfolio are now only -43 bp and -44 bp (t-statistics -0.91 and -1.03), less than a half of the CAPM alphas and way below the conventional levels of significance. The alphas of the second smallest portfolio see a comparable reduction. The negative size effect in the growth portfolio is reduced to -36 bp, t-statistic -0.71 and -41 bp, t-statistic -0.83 for equal-weighted and value-weighted returns, respectively, again more than 50% improvement over the CAPM alphas.

The aggregate volatility risk explanation of the small growth anomaly and the negative size effect is further supported by sizeable and highly significant BVIX betas of the respective portfolios. For example, the equal-weighted smallest growth portfolio has the BVIX beta of -0.461, t-statistic -2.96, and the arbitrage portfolio capturing the negative size effect in value-weighted returns boasts the largest BVIX beta value of -0.642, t-statistic -2.63.

Going back to the January 2001 problem, in Panel B I look how the BVIX factor performs if January 2001 is kept in the sample. To reiterate, keeping January 2001 provides the false impression that the small growth anomaly is weak in equal-weighted returns. However, even with January 2001 in the sample, I see sizeable reduction in the two small growth portfolios alphas after I add the BVIX factor. The absolute magnitude of the reduction is only slightly smaller than what I observe in the left panels. The BVIX betas of the small growth portfolios are also large and negative, though mostly insignificant, with the largest t-statistic of -1.84.

What is more important, the BVIX factor works great in value-weighted returns even if January 2001 is included. The CAPM alpha of the smallest growth portfolio (-93 bp per month, t-statistic -2.74) is reduced by more than a half to -44 bp, t-statistic -0.95 after I include BVIX. The ICAPM alpha also beats the Fama-French alpha (-65 bp, t-statistic -3.55) by a wide margin. The alphas of the second smallest growth portfolio and the negative size effect for growth firms see even greater reduction after I control for the aggregate volatility risk. The BVIX betas of the portfolios of interest are large, but only marginally significant, because January 2001 is still an outlier. For example, the smallest growth portfolio has the BVIX beta of -0.495 (t-statistic -1.96), followed by the second smallest growth portfolio with the BVIX beta of -0.374 (t-statistic -2.22).

Overall, comparing Panel A and Panel B suggests the simple power story. Keeping the outlier in the sample greatly inflates the standard errors and deprives me of the statistical power needed both to find the small growth anomaly and to find its explanation in equal-weighted returns. In value-weighted returns, the small growth anomaly remains strong even in the presence of the outlier, and is successfully explained by the BVIX factor. However, even in value-weighted returns the outlier is powerful enough to spoil the t-statistics of the BVIX betas. Similar comments apply to the negative size premium in the growth quintile.

In untabulated results, I also find that explaining the small growth anomaly helps to explain a part of yet another puzzle - the huge value effect for small firms. If I omit January 2001 from the sample, the part of the value effect unexplained by the CAPM in the lowest size quintile is 1.8% per month (t-statistic 5.72) and 1.56% per month (t-statistic 4.57) for equal-weighted and value-weighted returns, respectively. When I add the BVIX factor, the unexplained part of the value effect for smallest firms is reduced to 1.55% and 1.19% per month, t-statistics 4.74 and 2.94, which is close to what the Fama-French model produces.

2.4 The New Issues Puzzle

2.4.1 Can the BVIX Factor Explain the New Issues Puzzle?

Brav, Geczy, and Gompers (2000) show that about one half of IPOs and one quarter of SEOs are the firms in the smallest growth quintile. The previous section shows that the BVIX factor is successful in explaining the underperformance of this portfolio, increasing the *a priori* likelihood that the BVIX factor will explain the underperformance of IPOs and SEOs as well.

My explanation of the new issues puzzle is a firm-type story. I hypothesize that the new issues puzzle exists because stock happens to be issued by the type of firms (small growth), which is mispriced by the existing asset-pricing models. My story does not predict any change in risk around the issue date, but it does not exclude such possibility and can be complemented by a risk-shift story. Compared to Brav, Geczy, and Gompers (2000), who also argue that new issues are mispriced only because they are small growth, my paper makes a step ahead by suggesting a risk factor behind the small growth anomaly (and, consequentially, behind the new issues puzzle), which is what Brav, Geczy, and Gompers (2000) leave for further research.

The previous subsection warned that the power of the tests in my sample period is reduced by including January 2001 in the sample. The January 2001 problem is present in the new issues portfolios as well: the equal-weighted IPO portfolio earns 39.2% in January 2001, which is its maximum return in my sample period and about four times the average annual return to the portfolio. The equal-weighted SEO portfolio earns 23.9% in January 2001, which also its maximum return and about 2.5 times the average annual return.

In Table 9, I fit to the equal-weighted new issues portfolios the CAPM, the Fama-

French model, and the ICAPM with BVIX. The new issues portfolios consist of IPOs or SEOs performed from 2 to 37 months ago, and are rebalanced monthly. The month after the issue is skipped because of the well-known short-run IPO underpricing. The left part of the table presents the results with January 2001 dropped from the sample, and the right part keeps it in the sample.

The CAPM and Fama-French alphas in the left part of Panel A show that the IPO underperformance is strong in my sample period. The alphas are -70 and -54 bp per month, respectively, and the t-statistics are -2.27 and -2.97. When I augment the CAPM with the BVIX factor, the results change drastically: the alpha drops to -37 bp and it is no longer statistically significant (the t-statistic is -1.19). The drop in the alpha represents a 47% improvement over the CAPM and a 31% improvement over the Fama-French model. Expectedly, the BVIX beta is large, negative and significant (-0.376 with t-statistic -4.38).

The left part of Panel B deals with the SEO portfolio (with January 2001 omitted from the sample) and shows similar results. I start with the CAPM and Fama-French alphas of -51 bp and -49 bp per month (t-statistics -2.67 and -4.20), which are reduced by 46% and 44% respectively to the ICAPM alpha of -27 bp (t-statistic -1.37). The BVIX beta is -0.257 (t-statistic -6.09).

Overall, the BVIX factor does a very good job, reducing the alphas of the new issues portfolios by 31% to 47% and producing economically large and statistically significant negative BVIX betas. The negative BVIX betas reflect the hedging ability of new issues against aggregate volatility shocks, which is predicted by the model in the first chapter.

If I keep January 2001 in the sample, it reduces the power of my tests and slightly biases down the absolute magnitude of the alphas and the BVIX betas. In the right part of Table 9 I observe that with January 2001 in the sample the BVIX beta of IPOs is only marginally significant (t-statistic -1.99) and their Fama-French alpha is also marginally significant with t-statistic of -2.11. The results for SEOs are more robust, because the January 2001 problem is weaker for them. However, the values of the BVIX betas, the absolute and relative reduction of alphas after I add the BVIX factor are similar to what I see in the left part of the table. Therefore, keeping January 2001 in the sample does not change the tenor of my results, it only spoils the statistics somewhat, as predicted by the power story.

To check the robustness of my results, I repeat the analysis for value-weighted returns

(results not reported to save space). The value-weighted SEO portfolio returns produce exactly the same results as the equal-weighted returns, with slightly more significant BVIX betas. The value-weighted IPO returns also produce more significant BVIX betas, but the alphas are positive for all models except for the CAPM, where the alpha is negative, but insignificant. It implies that the IPO underperformance in value-weighted returns is absent in my sample period, even though IPOs still have significantly negative BVIX betas because they are small.

Loughran and Ritter (2000) argue that weighting equally each firm rather than each period produces a more powerful test of the new issues underperformance. They point to the widely known IPO and SEO cycles and the stronger underperformance of new issues after "hot markets" with high volume of issuance. If the cycles represent something like the waves of sentiment and new issues are more overpriced when investors are more excited, weighting each period equally is incorrect, because it puts relatively smaller weights on the issues after "hot markets", when the mispricing actually occurs.

This suggestion is debated by Schultz (2003), who proposes the pseudo market timing story. Schultz hypothesizes that firms are more likely to issue equity when prices are high. Then issues will cluster at peak prices and subsequently underperform in event-time, even if the market is efficient and the managers have no market timing ability. Schultz (2003) shows that calendar-time regressions, like the OLS I performed above, eliminate the pseudo market timing bias, and the WLS regressions proposed in Loughran and Ritter (2000) increase the bias.

As a robustness check, I follow Loughran and Ritter (2000) and re-estimate all my models using weighted least squares with White (1980) standard errors (results not reported for brevity). The weight is the number of issuing firms in each period. I find that using the WLS with White standard errors greatly increases all t-statistics, slightly increases the SEOs alphas and almost doubles the IPOs alphas. The BVIX betas estimated with WLS have absolute magnitude of t-statistics above 3.9 in all specifications, but the magnitude of the BVIX betas increases only slightly. The WLS alphas sometimes remain marginally significant even after I control for the BVIX factor, but the relative reduction is very close to what it was in Table 9. I conclude that using the weighting scheme proposed by Loughran and Ritter (2000) does not influence my results in a material way.

2.4.2 The BVIX Factor versus the Investment Factor

A recent paper, Lyandres, Sun, and Zhang (2007), shows that the new issues underperformance can be reduced by about 80% if one controls for the investment factor. The investment factor is a zero-cost portfolio long in bottom 30% and short in top 30% of firms sorted on the investment-to-assets ratio. Lyandres, Sun, and Zhang (2007) point out that the firms with low expected returns tend to invest more and therefore have to issue equity. This behavior explain both the positive abnormal returns to the investment factor and the negative abnormal returns to the new issues portfolios.

My explanation of the new issues puzzle based on aggregate volatility risk does not imply that the investment factor should be subsumed by the BVIX factor. The investment factor is a completely different explanation, which can cooperate well with the BVIX factor in explaining the new issues puzzle. Yet, the results in Lyandres, Sun, and Zhang (2007) seem to imply that there is no room for other factors in explaining the IPO/SEO underperformance, because the investment factor explains the whole puzzle.

In this subsection, I show that the extraordinary performance of the investment factor is driven primarily by the January 2001 problem. With January 2001 removed from the sample, it outperforms the BVIX factor only marginally. Moreover, I find that the explanatory power of the two factors is non-overlapping and they are able to cooperate successfully without diminishing each other's importance. Using both factors to explain the new issues puzzle makes the alphas of the IPO and SEO portfolios exactly zero.

The preliminary analysis (not reported) shows that the investment factor and the BVIX factor are totally uncorrelated. The correlation between them is only 0.058. When I try to use either of them, alone or in combination with other factors, to explain the returns of the other, the beta and the t-statistic, as well as the reduction in the alpha, are extremely small.

The idea behind the investment factor is simple: high investment firms are likely to have low expected return, which makes them invest more. One can remain agnostic about why the expected return is low and still use the investment factor. The existing risk stories behind the investment factor (Xing, 2007, Li, Livdan, and Zhang, 2007) argue that it measures Tobin's Q. However, it is clearly only a part of the story, because the overlap between the investment factor and the HML factor, which also looks at something similar to Tobin's Q, is small. It is even possible that the investment factor proxies for some

economy-wide mispricing, as Titman, Xie, and Wei (2004) would suggest.

The Tobin's Q story behind the investment factor implies that BVIX and the investment factor should overlap, as BVIX and HML do (see the first chapter). It is unclear, though, what other possible stories behind the investment factor would suggest about its relation to BVIX. My results suggest that the joint effect of all forces behind the investment factor make it unrelated to BVIX.

In Table 10, I estimate the ICAPM with the BVIX factor, the investment factor or both. The left part of the table reports the results with January 2001 excluded from the sample. For the equal-weighted IPO portfolio in Panel A, the ICAPM with the BVIX factor or the investment factor produces insignificant alphas of -37 bp and -33 bp per month, respectively (t-statistics -1.19 and -1.03). In the ICAPM with both factors, their betas hardly change at all and remain highly significant, and the IPO portfolio alpha goes to -0.3 bp per month.

The 53% improvement in the alpha caused by adding the investment factor is quite different from the results in Lyandres, Sun, and Zhang (2007), where the investment factor explains 80% of the IPO underperformance. The cause of the difference is only one observation - January 2001. When I include it in the sample in the right part of Table 10, the investment beta increases by more than one third, and the alphas become very close to zero. The CAPM augmented with the investment factor now shows 85% improvement over the regular CAPM.

However, even with January 2001 in the sample adding the BVIX factor alongside with the investment factor does not change their betas at all, and the BVIX factor still attains the alpha change of the same absolute magnitude as when it is added alone. It confirms that the investment story and the aggregate volatility risk story are two completely independent and equally useful explanations of the IPO underperformance.

The results for the SEO portfolio in Panel B are very similar. With January 2001 excluded, the investment factor outperforms the BVIX factor by about one third (65% reduction in the CAPM alpha versus 46% reduction). The reduction in the alpha and the magnitude of the investment beta increase greatly if I add January 2001 back. Still, with January 2001 or without, the BVIX beta and the explanatory power of the BVIX factor do not change a bit after the investment factor is added together with the BVIX factor. With January 2001 excluded and both factors in the regression, the CAPM alpha goes to

+5 bp per month, and with January 2001 included the CAPM alpha is +15 bp per month.

I also checked the robustness of my results to using value-weighted returns and/or running WLS instead of OLS. The main conclusion is robust to using WLS. The BVIX factor and the investment factor are about equally important in explaining the new issues puzzle. Adding them together in the CAPM does not change their explanatory power, but significantly improves the performance of the model compared to when the factors are used alone. The results of the robustness check are not reported to conserve space.

The overall conclusion is that, first, the investment factor and the BVIX factor provide totally independent and equally important explanations of the new issues puzzle. Using them together explains 100% of the puzzle. Second, the results in Lyandres, Sun, and Zhang (2007) are sensitive to excluding January 2001 from the sample. In untabulated findings, I mimic their results for their sample period and find that if I exclude January 2001, the results are pretty close to what I show in my sample period - i.e. without January 2001, the investment factor explains 50% of the new issues puzzle, not 80%.

2.4.3 The New Issues Puzzle in Cross-Section

Several studies have noted that the new issues underperformance depends on size and market-to-book. For example, Loughran and Ritter (1997) show that small firms underperform more than large firms, and Eckbo, Masulis, and Norli (2000) shows that growth firms underperform more than value firms.

This pattern is entirely consistent with the model in the first chapter. The model predicts that small growth firms have low expected returns, because they are good hedges against aggregate volatility increases. It also predicts that IPOs and SEOs, which often are small growth firms, earn negative abnormal returns in the existing asset-pricing models. If one takes my model to the extreme, it would suggest that small growth new issues should be driving the new issues puzzle, and it should be absent for other issuers.

The stories behind the investment factor also can generate predictions about the cross-section of the new issues puzzle. Under the Q-story, the investment factor betas should be more negative for the firms that have abundant low-risk projects. The Q-theory predicts that it should be growth firms and, possibly, small firms. Under underreaction stories, the investment factor can measure the tendency of the management to build empires and squander free cash that comes from the issue. The negative investment beta then means

more of such behavior for the firm, and large and value firms should therefore have the most negative investment betas.

In Table 11 I explore whether the new issues in my sample underperform more if the issuers are small or growth, and whether this underperformance can be explained by the BVIX factor, as my model predicts, or by the investment factor. I look at single sorts, because the number of firms in the new issues portfolio does not allow drawing reliable conclusions from sensible double sorts. In sorting the firms by size and growth I first require the implied strategies to be tradable. Also, the intersecting periods of sorting into size portfolios and measuring returns would create mechanically larger underperformance for smaller firms. They would possibly be ranked as small because they lost value in the first months after the issue. To avoid it and to make the portfolios tradable I have to measure the book value and the market value in the month after the issue or earlier.

Second, I prefer to use the after-issue values of book and market to make smaller a possible mechanical relation between the size of the issue and the underperformance. It is known that small and growth firms issue relatively more (see, e.g., Lyandres, Sun, and Zhang, 2007). Under the behavioral stories more raised funds mean more funds for the managers to squander and more bad news for the investors to underreact to.

All that leads me to use the market value after the offer and the common equity after the offer from the SDC database to sort my firms into size and market-to-book portfolios. I first sort the whole CRSP population into three size or market-to-book groups - top 30%, middle 40%, and bottom 30% - using NYSE (`exchcd=1`) breakpoints. Then I use the breakpoints to form the same three size and market-to-book groups in my new issues sample. The results are robust to using CRSP breakpoints.

Size and market-to-book are strongly positively related in cross-section. I predict the underperformance to be stronger for growth firms and small firms. But small firms are usually value firms, which can obscure the relation between size and the underperformance. To avoid that, I make the size sorting conditional on market-to-book, that is, I determine the size breakpoints separately for each market-to-book decile. This sorting procedure does not qualitatively change my results, but makes them a bit cleaner.

In Table 11 I report the results of fitting the ICAPM with the BVIX factor, the investment factor, both, or none (in which case it is the usual CAPM) to new issues portfolios in each size or market-to-book group. To save space, I only report the four

(I)CAPM alphas, and the BVIX betas and the investment betas when the factors are used separately (as in the previous subsection, the betas do not change if I use both factors in one regression).

In Panel A of Table 11 I look at equal-weighted returns to the IPO portfolio. The sample period does not include January 2001. Including it, as usual, deteriorates the power of the tests somewhat and makes the investment factor uniformly stronger, but does not change the tenor of my results.

I first notice that, consistent with the existing evidence and the prediction of my model, small and growth IPOs underperform by a lot, whereas large and value IPOs do not underperform at all. The new issues in the large and value portfolios have insignificantly positive alphas, compared to significant negative alphas of -77 bp and -97 bp per month of new issues in the small and growth portfolios, respectively. The difference between the alphas is 1.18% per month for the market-to-book sorting and 1.03% per month for the size sorting (t-statistics 3.68 and 2.40, respectively). Using the Fama-French model instead of CAPM (results not reported) makes the alphas of the small and growth new issues and the difference in the alphas a bit smaller, but does not change the tenor of my results.

As predicted by my model, adding the BVIX factor greatly reduces the underperformance of the growth IPOs and small IPOs. The alpha of the growth IPOs is reduced from -97 bp to -53 bp per month (45% reduction), and the alpha of the smallest IPOs is reduced from -77 bp to -42 bp per month (46% reduction). Both ICAPM alphas have the absolute value of t-statistic less than 1.4. Adding the BVIX factor also makes the difference between the alphas of growth and value (small and large) IPOs smaller by 27% and the difference becomes insignificant for the size sorts.

The aggregate volatility risk explanation of the small and growth IPOs underperformance and its difference from the performance of large and value IPOs is supported by the BVIX betas. Small and growth IPOs have the BVIX betas of -0.393 and -0.490, both highly significant, compared to the BVIX betas of large and value IPOs of -0.111 and -0.169. The difference between the BVIX betas is economically large and highly significant (t-statistics 2.54 and 3.02 for size and market-to-book sorts, respectively).

When I look at the ICAPM with the investment factor, I first notice that, quite surprisingly, the investment betas are flat in the market-to-book sorts. In the size sorts, the smallest stocks have the second largest investment beta, surpassed by the investment

beta of mid-size IPOs. Consequentially, the investment factor explains the extreme underperformance of the small and growth IPOs much worse than the BVIX factor. The investment factor also does not explain at all the underperformance differential between growth and value IPOs and contributes insignificantly to explaining the differential between small and large IPOs. The ICAPM with the investment factor also fails in a rather strange way, producing the marginally significant positive alpha for value IPOs (51 bp per month, t-statistic 1.77).

When I use the BVIX factor and the investment factor together, the alpha differential between small and large IPOs decreases even more and becomes clearly insignificant (t-statistic 1.43). The negative alphas become very close to zero from large, but insignificant values they have when BVIX or the investment factor are used alone. However, the positive alphas of the value IPOs and large IPOs increase even more and become more significant (63 bp, t-statistic 2.26, and 54 bp, t-statistic 1.80, respectively).

In Panel B, I repeat the analysis for SEOs. Analogous to IPOs, I find that small and growth SEOs have more negative CAPM alphas than large and value SEOs, but the difference is much smaller. For the market-to-book sorts, the alphas differ by 67.5 bp per month, t-statistic 2.90, and for the size sorts they differ by 33 bp, t-statistic 1.36. Contrary to IPOs, large SEOs still underperform - their alpha is -24 bp per month, t-statistic -1.74.

I find that small and growth SEOs have large and significantly negative BVIX betas and large and value SEOs have BVIX betas very close to zero. The difference in betas is statistically significant at about 0.3 for both the market-to-book sorts and the size sorts. It explains why the BVIX factor can explain away both the underperformance of small and growth SEOs and its difference from the performance of large and value SEOs. The alpha of the growth SEOs is reduced from -74 bp, t-statistic -3.01, to -37 bp per month, t-statistic -1.36 (50% reduction) and the alpha of the small SEOs is reduced from -57 bp, t-statistic -2.44, to -30 bp per month, t-statistic -1.14 (48% reduction) after I add the BVIX factor. The underperformance differential between value SEOs and growth SEOs drops to 36 bp, t-statistic 1.40 (46% reduction), and the differential between small SEOs and large SEOs reduces to 6 bp, t-statistic 0.19 (83% reduction).

The investment betas of large and small SEOs, as well as value and growth SEOs, are no different. That is why the investment factor does not contribute at all to explaining the differential in their performance and leaves the alpha of growth SEOs marginally significant

at 10% (-43 bp, t-statistic -1.7).

When I use the BVIX factor and the investment factor together, the underperformance of the SEOs in all size and market-to-book groups is explained perfectly, as well as the differential between small and growth SEOs and large and value SEOs. While the investment factor does not contribute to explaining the differential, it helps the BVIX factor to explain the underperformance of large SEOs (the alpha is reduced from -24 bp, t-statistic -1.67, to -1 bp, t-statistic -0.08).

To sum up, the BVIX factor turns out very helpful in explaining the cross-section of the new issues puzzle. The variation in its betas is significant and large enough to explain the abysmal performance of small and growth new issues, and its difference from quite normal performance of large and value new issues. The investment factor, while useful in explaining the alphas in all size and market-to-book groups, is quite helpless in explaining why the performance of small and growth new issues differs from that of large and value new issues.

2.4.4 Event-Time Regressions

It is widely known that the new issues underperformance changes through time, peaking in the second year after the issue and disappearing after five years (see, e.g. Ritter (2003) and references therein). The story behind the BVIX factor is a firm-type story and therefore neither implies nor excludes the risk shift that is needed to explain the change in underperformance as the new issue ages.

In the first chapter I show that the effect of idiosyncratic volatility comes through growth options, that is, idiosyncratic volatility reduces expected returns more if there are more growth options. If the firm spends a significant part of the issue proceeds on R&D right after the issue and accumulates growth options in the first year, and then starts extinguishing them, there can be some risk shift in the direction of the observed pattern in underperformance.

In this subsection I disaggregate the 36-month IPO/SEO portfolios into six event-time portfolios, which include the returns to the stocks issued from 2 to 7 months ago, from 8 to 13 months ago, etc. The portfolios are rebalanced monthly. I treat each of the six portfolios separately to see the evolution of the alphas and betas as the issue ages.

In Panel A I look at the IPO portfolios. Looking at the CAPM alphas in the top

row, where no additional factors are added, I observe the well-known pattern: the IPO underperformance is most severe in the second half of the first year and in the second year. Unlike previous studies such as Loughran and Ritter (1995) and Ritter (2003), I find marginally significant (at 10% level) negative returns even in the first six months, which are usually called the "honeymoon" period without underperformance. This result is partially driven by omitting the first month after the issue. I also find that the underperformance lasts only for 30 months, whereas Loughran and Ritter (1995) find some underperformance even in the fifth year after the issue.

The cursory glance at the alphas I estimate in the ICAPM with either of the factors shows that the alphas go down uniformly for all portfolios. All alphas except for the months 8-13 and 14-19 become insignificant from previously significant values as I add either of the factors. It is comforting in the sense that the added factors have significant explanatory power for all the six-month portfolios, and the results in the previous tables are not driven by extremely good performance in one or two of the post-event periods. I observe that the alphas from the ICAPM with investment factor are somewhat smaller than the alphas from the ICAPM with BVIX when the underperformance is most severe.

This pattern is further confirmed by looking at the factor betas. The BVIX betas seem pretty flat, with a slight -0.061 decrease between the months 2-7 and 8-13 and a small 0.119 increase between the months 8-13 and 26-31. The investment betas show a well-expressed risk shift. The investment beta shifts from -0.466 in months 2-7 to -0.727 in months 8-13 and stays at this level for another 12 months. Then it jumps back to -0.434 in months 32-37. However, this risk-shift can only explain why the underperformance is stronger in months 8-25, but not why it dissipates completely after 30 months.

The fact that the investment factor still leaves significant IPO underperformance between the 8th and the 19th month is at odds with what Lyandres, Sun, and Zhang (2007) find in their Figure 2. The explanation is the January 2001 problem, which is most severe exactly for these two event-time portfolios. For example, the IPO portfolio composed of 14 to 19 month old issues earned 50.5% in January 2001, compared to only 18.7% earned in the same month by the 2 to 7 month old issues.

In the last row, I look at the performance of the ICAPM with both the BVIX factor and the investment factor. When the factors work together, they are able to explain away the IPO underperformance for all portfolios. The largest negative alpha (14 to 19 month

old issues) is -41 bp, t-statistic -1.27.

Most of the results from Panel A carry on to Panel B, where I look at the SEO portfolios. The underperformance of the SEOs in my sample peaks earlier, in the second half of the first year, and both factors alone fail to explain it, but are able to make it together. The SEO underperformance also disappears earlier, after only two years. The investment factor is more successful in the first half of the second year (months 13-19), when the BVIX factor still fails to make the alpha insignificant. Overall, the explanatory power of both factors is significant in all periods, as confirmed by large negative and significant factor betas.

As for the risk shift, I observe that the BVIX beta becomes less negative uniformly from the first subperiod to the last, but the magnitude of the change is only 0.132. The investment beta again demonstrates the desired risk decrease in the months 14-25, lagging somewhat the pattern in alphas, and becomes small and insignificant by the end of the third year.

Overall, it seems that the investment factor is a much better candidate for a risk-shift story needed to explain why the new issues underperformance changes in event time. The BVIX factor, expectedly, has only limited ability to produce risk shifts, but it is significantly useful in all event-time periods and is essential in reducing all alphas to zero. The firm-type story (BVIX) and the risk-shift story (the investment factor) therefore coexist in the data and are both important in explaining the new issues underperformance.

2.5 The Cumulative Issuance Puzzle

2.5.1 The Definition and Descriptive Evidence

In a recent paper, Daniel and Titman (2006) establish the cumulative issuance puzzle, defined as the negative return differential between the firms with the most positive and the most negative net equity issuance. Daniel and Titman define cumulative issuance for a firm as the part of the market capitalization growth unexplained by prior returns. In empirical tests they measure this part as the difference between the log market capitalization growth and the log cumulative returns in the past five years. According to Daniel and Titman, the negative relation between cumulative issuance and future returns means that managers make use of the windows of opportunity, created by investors' underreaction to intangible information. Managers issue overvalued stock that subsequently loses value, and retire

undervalued stock that subsequently performs well.

The cumulative issuance variable is a catch-all proxy for all types of issuance activity, including stock grants, stock-for-stock mergers, dividends paid in kind, etc. It also includes events like repurchases, which make cumulative issuance negative if they prevail. Clearly, the cumulative issuance puzzle does not intersect with the IPO underperformance, because a firm has to be public for at least 5 years to have the measure of the cumulative issuance. The cumulative issuance puzzle can be correlated with SEO underperformance, but Daniel and Titman show that in cross-sectional regressions the SEO dummy does not subsume the cumulative issuance effect on future returns.

In this section, I hypothesize and show that the cumulative issuance puzzle is explained by the aggregate volatility risk exposure, as the IPO and SEO underpricing is. My story is that issuing firms are usually small and growth, and therefore provide a hedge against aggregate volatility increases for the reasons explained in Section 9 and in the first chapter.

The missing link here is demonstrating that firms with high cumulative issuance are predominantly small and growth. This is what I show in Table 13. In Panel A, I sort the firms on cumulative issuance into five quintiles and report the size and market-to-book at the portfolio formation date. Size and cumulative issuance are measured annually in December, and the market-to-book is from the $t-1$ fiscal year, if the fiscal year end is in June or earlier, and from the $t-2$ fiscal year, if the fiscal year end is in July or earlier. Because all measures are annual, I have only 21 observation between 1985 and 2005.

Panel A of Table 13 shows that high issuance firms are indeed much smaller and much more growth-like than low issuance firms. Firms in the highest issuance quintile have the average capitalization of \$1.057 bln and the average market-to-book of 5.425 versus the \$2.535 bln capitalization and the 2.5 market-to-book in the lowest issuance quintile. The differences are highly statistically significant even for the small time-series sample.

In Panel B I report the average cumulative issuance measure for 25 size - market-to-book quintiles. In each market-to-book quintile I see strong, significant and mostly monotone increase in cumulative issuance from large to small caps. Similarly, in each size quintile I observe strongly significant and generally monotone increase in cumulative issuance from value to growth. Overall, the bottom left corner, where the small growth firms are, sees cumulative issuance of half or even more of the firm value in the past 5 years. The top right corner, where large value firms are, demonstrates close to no net

issuance at all.

I conclude that the evidence in Table 13 supports the hypothesis that firms with high cumulative issuance are usually small growth. It makes me optimistic about the ability of the BVIX factor to at least partly explain the cumulative issuance puzzle.

2.5.2 Explaining the Cumulative Issuance Puzzle

Lyandres, Sun, and Zhang (2007) also address the cumulative issuance puzzle. They show that the zero-cost arbitrage portfolio long in top 30% issuance firms and short in bottom 30% issuance firms has negative investment factor betas. However, the betas are only large enough to explain about 40% of the puzzle, leaving a statistically significant portion unexplained.

In Table 14, I show the results of fitting the ICAPM with either the BVIX factor, or the investment factor, or both to the cumulative issuance arbitrage portfolio. Panel A looks at equal-weighted returns, and Panel B deals with value-weighted returns. As usual, I report the results with January 2001 omitted from the sample in the left part of each panel and the full sample results in the right part. In January 2001, the cumulative issuance arbitrage portfolio makes 25% return, which shows as a clear outlier on the histogram.

Panel A of Table 14 shows that adding the BVIX factor reduces the arbitrage portfolio alpha by more than 40% and makes it insignificant, irrespective of whether January 2001 is in the sample. The BVIX beta of the arbitrage portfolio is negative and highly significant at -0.339 (t-statistic -3.45), confirming that high issuance firms are a hedge against aggregate volatility risk. Keeping January 2001 in the sample reduces the BVIX beta t-statistic to -2.09, but the beta magnitude and the alpha reduction are not influenced.

The investment factor, however, performs much worse. If January 2001 is omitted from the sample, adding the investment factor reduces the cumulative issuance alpha only by 29%, leaving it statistically significant with t-statistic -2.25. The investment beta is large and negative, but also lacks significance. If January 2001 is kept in the sample, the significance of the investment beta improves somewhat, making it marginally significant at 10% level. Keeping January 2001 also greatly improves the impact of the investment factor on the alpha, making it insignificant and bringing its reduction from 29% to 46%, which is close to 40% reported in Lyandres, Sun, and Zhang (2007). It again implies that a big part of the successful performance of the investment factor in Lyandres, Sun, and

Zhang (2007) is likely to be driven by one data point.

When I use the BVIX factor and the investment factor together, they hardly influence each other's explanatory power, defined either as the factor beta or the alpha reduction. Using both factors together brings the alpha of the cumulative issuance arbitrage portfolio to as low as -20 bp per month (t-statistic -0.85) without January 2001 and -7 bp per month (t-statistic -0.29) with January 2001.

In Panel B I look at value-weighted returns. If BVIX is useful in explaining the cumulative issuance puzzle because it resolves the small growth anomaly, I expect its impact to be smaller in value-weighted returns, because they are dominated by mega-caps. Value-weighting had a smaller impact for new issues, which are almost never mega-caps, but the cumulative issuance measure is computed for the whole CRSP population.

Panel B shows that my concerns are valid: the BVIX factor beta is reduced by two thirds compared to what it was in Panel A, and its impact on alpha goes down to 18% reduction only, which leaves the alpha significant. If January 2001 is included in the sample, the BVIX beta loses significance, but its impact on alpha hardly changes.

The investment factor, which was shown to better explain the returns to large new issues, expectedly performs better in value-weighted returns. Its beta increases by a half compared to equal-weighted returns, and the investment factor reduces the alpha by more than 50%, leaving it, nevertheless, significant. The investment beta and the alpha reduction are increased further if I keep January 2001 in the sample.

Even though the BVIX factor is weak in value-weighted returns, it is still essential in explaining the cumulative issuance puzzle, because only the ICAPM with both BVIX and the investment factor makes the value-weighted alphas clearly insignificant.

2.5.3 The Cross-Section of the Cumulative Issuance Puzzle

Similar to the analysis in the previous section, in Table 15 I look at the cross-section of the cumulative issuance puzzle and whether the BVIX factor and the investment factor can explain it. The hypothesis is again that the cumulative issuance puzzle should be stronger for growth firms and small caps, because my story suggests that the cumulative issuance puzzle is driven primarily by these firms.

Because of the strong relation between size and market-to-book, in Table 15 I make the size sorts conditional on market-to-book. I first sort the firms into market-to-book deciles,

and then within each decile sort them on size into top 30%, middle 40%, and bottom 30%. The market-to-book deciles are then merged into the same three groups - top 30%, middle 40%, and bottom 30%.

In Table 15 I look at equal-weighted returns (January 2001 is dropped from the sample) and find that, consistent with my intuition, the cumulative issuance puzzle is limited to the top 30% growth firms. For them the alpha of the cumulative issuance arbitrage portfolio is -1.15% bp per month (t-statistic -2.71), while for value firms the alpha is insignificantly positive at 3.5 bp, and for the neutral firms the alpha is -41 bp and marginally significant at the 10% level. The difference in the cumulative issuance alpha between growth and value is 1.18% per month (t-statistic 4.29).

After I control for the BVIX factor, the huge cumulative issuance alpha for growth firms is reduced by 57% and becomes insignificant, and the difference in the alphas between value and growth decreases by 41% and becomes only marginally significant at the 10% level. The BVIX betas of the cumulative issuance arbitrage portfolios vary from -0.183, t-statistic -3.74, for value firms to -0.699, t-statistic -3.05, for growth firms. It supports my claim that the cross-section of the cumulative issuance puzzle and the puzzle itself are driven by aggregate volatility risk.

The investment factor, however, is helpless at explaining either the negative cumulative issuance alpha in the growth portfolio or the difference in the alphas between value and growth. The investment betas are insignificant and flat across the market-to-book portfolio. Including January 2001 (results not reported) increases the significance of the investment betas and their impact on the alphas, but the conclusion that the investment factor is no good at explaining the cross-section of the cumulative issuance puzzle remains.

In the size sorts I fail to find any difference in the cumulative issuance puzzle between small caps and large caps. Surprisingly, mid caps beat them both by a factor of two, with cumulative issuance alpha of -97 bp per month (t-statistic -3.61). Yet, the BVIX factor is successful in handling this pattern in alphas as well, because the mid caps have the same BVIX beta as the small caps (both betas are highly significant at -0.36). The alpha of the mid caps decreases by 34% and becomes marginally significant after I add BVIX.

The investment factor fails to explain the worst case of the cumulative issuance puzzle, decreasing the alpha in the mid cap portfolio by only 19% and leaving it highly significant. The investment beta increases from zero for small caps to an insignificant value for mid-caps

and to -0.527 (t-statistic -3.18) for large caps. Using the BVIX factor and the investment factor together is the best, because it reduces the alphas among small caps and large caps to zero, and the mid-caps alpha is only marginally significant at the 10% level.

The overall conclusion is that the cross-section of the cumulative issuance puzzle is driven by growth firms, as the aggregate volatility risk story predicts. The BVIX factor is successful in explaining the cross-section of the cumulative issuance puzzle and in explaining its most severe cases. The investment factor appears to be surprisingly more helpful for large caps, which are not likely to be heavily investing firms.

2.6 Conclusion

The paper tests whether aggregate volatility risk is an explanation of the small growth anomaly, the new issues puzzle and the cumulative issuance puzzle in Daniel and Titman (2006). The motivation is the model in the first chapter, which predicts that high idiosyncratic volatility growth firms (which are also small growth) offer an important hedge against aggregate volatility increases and associated risk premium increases. My story for the new issues puzzle and the cumulative issuance puzzle is a firm-type story: I hypothesize that these puzzles arise because issuers happen to be mostly small growth, the firm type that earns the lowest abnormal returns according to the existing asset-pricing models.

I measure the aggregate volatility risk exposure by regressing returns on the BVIX factor. The BVIX factor is long in the firms with the most negative return sensitivity to aggregate volatility increases and short in the firms with the most positive return sensitivity. The ICAPM with the BVIX factor improves significantly over the CAPM and even over the Fama-French model in pricing different portfolio sets. The BVIX betas are significant for many portfolios. The ICAPM with BVIX explains the small growth anomaly and the negative size effect in the lowest book-to-market quintile. It reduces the respective alphas by more than a half compared to the CAPM and the Fama-French model and pushes the t-statistics well below all conventional levels of significance. The BVIX factor is also useful to dampen the large abnormal value effect for the smallest stocks.

The tests of the aggregate volatility risk explanation for the new issues puzzle are also extremely successful. For both IPOs and SEOs, augmenting the CAPM with the BVIX factor reduces the new issues alphas by about 45% relative to either the conventional

CAPM or the Fama-French model and makes the alphas insignificant. The large and significantly negative BVIX betas of the new issues portfolios confirm my hypothesis that new issues earn low returns, because they are good hedges against adverse aggregate volatility shocks.

An interesting by-product of my tests is the January 2001 problem. In January 2001, the smallest growth stocks earned a huge 55% return. In the same month, IPOs gained 39% and SEOs made 24%. This sole data point has the ability to bias the estimates and reduce the power of all tests dealing primarily with the smallest growth stocks. A case in point is the Lyandres, Sun, and Zhang (2007) paper, which claims that the investment factor can explain about 75% of the new issues underperformance. I show that in my sample period it performs even better if I keep January 2001 in the sample, but its explanatory power is reduced from 80% of the puzzle to 50% if I drop January 2001 from the sample.

The investment story and the aggregate volatility risk story seem to be completely unrelated and work great together. The explanatory power of the BVIX factor is not reduced at all if the investment factor is included in the same factor model. The same is true about the investment factor. When both factors are used to augment the CAPM, they are able to reduce the new issues underperformance to exactly zero.

I study the new issues puzzle in cross-section and find, consistent with the model in the first chapter and existing empirical studies, that the IPO and SEO underperformance is stronger for small firms and growth firms. The new result is that this difference in underperformance can be explained by different exposure to aggregate volatility risk. The ICAPM with the BVIX factor explains the abnormally low returns to small and growth IPOs/SEOs, as well as the difference between them and the returns to large and value IPOs/SEOs. Surprisingly, the investment factor is helpless in explaining the cross-section of the new issues puzzle, because the investment betas of new issues are unrelated to either their size or their market-to-book.

In event-time, I find that the BVIX factor is equally useful in reducing the alphas in all event periods. The investment factor captures the risk shift better, explaining why the new issues underperformance peaks in 6 to 24 months after the issue. However, even in this period the investment factor needs the help of BVIX to explain the underperformance.

The BVIX factor is also useful in explaining the low returns to the stocks with the highest cumulative issuance. I show that high issuance stocks are primarily small growth.

In equal-weighted returns, BVIX is able to explain 40% of the cumulative issuance puzzle, while the investment factor performs much worse in my sample period with January 2001 dropped from the sample. The investment betas are insignificant, and the alpha of the zero-cost portfolio long in the highest and short in the lowest cumulative issuance firms is reduced by 30% and remains significant. In value-weighted returns, which downplay the role of small firms, the BVIX factor and the investment factor change places in terms of their role in alpha reduction. However, even in value-weighted returns BVIX remains essential for making the alphas insignificant.

I also find that the cumulative issuance puzzle is higher for growth firms, but not for small firms (but rather for mid-caps). The BVIX factor produces the betas consistent with the cross-section of the cumulative issuance puzzle and successfully explains it where it is the strongest. The investment factor again produces the beta patterns that are not in line with the cross-section of the puzzle, with the investment beta being the strongest for the cumulative issuance portfolio in the large cap group.

3 Robustness Checks and Alternative Explanations

3.1 Introduction

This chapter collects robustness checks and tests for alternative stories mainly for the results in the first chapter. I start with revisiting the evidence presented in Bali and Cakici (2007), who argue that the idiosyncratic volatility discount is not robust to reasonable changes in the research design. I find that their most decisive results suffer from selection bias. When Bali and Cakici (2007) look at NYSE only firms, they use the current listing instead of the listing at the portfolio formation date. The selection bias is more severe for high volatility firms, which are more likely to perform very well or very poorly and move between exchanges. I find that Bali and Cakici (2007) overestimate the return to the highest volatility NYSE firms by more than 50 bp per month. It explains why they do not find any difference between the returns to the highest and lowest volatility firms in what they call the NYSE only sample.

Because the main mechanism in my model can work for any real option, not necessarily growth options, I also look at the interaction between the effects it predicts and the effects predicted by the Johnson model, which takes a similar approach and considers the interaction between leverage and analyst disagreement. I find that leverage and market-to-book are negatively correlated, which means that either growth options or the default option is out of the money. I do discern some joint impact of leverage and idiosyncratic volatility on expected returns, but only when I control for the interaction of market-to-book and idiosyncratic volatility. In short, I find that my results are clearly not driven by the effect in Johnson (2004). Rather, these effects run in the opposite direction, are much weaker than what my model captures, and are discernable only after I control for the volatility - market-to-book interaction that is at the heart of my model.

I also look at the relation between investment and the idiosyncratic volatility discount. I find that investment acts as a close empirical substitute for market-to-book. In the double sorts on investment and volatility, the idiosyncratic volatility discount increases with investment, and the investment anomaly increases with idiosyncratic volatility. Both these patterns line up quite well with the pattern in the BVIX betas, again consistent with my model and the hypothesis that investment just proxies for market-to-book. The only difference is that the low minus high investment arbitrage portfolio in the lowest volatil-

ity quintile has a significantly negative BVIX beta, and on average across all volatility quintiles the investment arbitrage portfolio has a zero BVIX beta, which explains why the investment factor and the BVIX factor turn out to be orthogonal in the second chapter. The value effect on average has an aggregate volatility risk part just because, absent idiosyncratic volatility, the return spread created by market-to-book is unrelated to aggregate volatility risk, and then the interaction between growth options and idiosyncratic volatility places the aggregate volatility risk part on top of it. Absent idiosyncratic volatility, the return spread created by investment is negatively related to aggregate volatility risk for some reason outside of my model and my study, and on average this effect and the aggregate volatility risk part from the interaction of growth options and idiosyncratic volatility cancel out.

I also perform a robustness check on the BVIX factor ability to explain the anomalies in the first and the second chapter. I try holding the VIX sensitivity portfolios the BVIX factor is long and short in for twelve months instead of one month, and for eleven months skipping the month after the portfolio formation (i.e. the only month BVIX uses in the baseline case). I also try estimating the return sensitivities to VIX changes using the data from the previous twelve months, not one, and hold the portfolios for twelve months after. All results in the previous two chapters are remarkable robust to those changes I make to BVIX.

Nagel (2004) and Boehme, Danielsen, Kumar, and Sorescu (2006) find that the idiosyncratic volatility discount is higher if limits to arbitrage are high. I show that my result that the idiosyncratic volatility discount exists only for growth stocks is distinct from theirs. In cross-sectional regressions, controlling for the product of limits to arbitrage and idiosyncratic volatility does not subsume the product of market-to-book and idiosyncratic volatility. However, the reverse is true as well, which means that while my result is not behavioral results repackaged, I cannot explain with my model how they come to arise. It is also confirmed by the BVIX betas from portfolio sorts, which are unrelated to limits to arbitrage. In portfolio sorts, the link between the idiosyncratic volatility discount and limits to arbitrage disappears after I control for the known risk factors.

Another way to test the behavioral stories is to look at the announcement effects. I test to see if an abnormally large chunk of the idiosyncratic volatility discount, or its relation to market-to-book, or the value effect, or its relation to volatility realized around earnings

announcements, and if it can be explained by the risk shift at or after the announcement. My model would predict such a risk-shift, because uncertainty (that creates the hedge through growth options) is high at the announcement and low afterwards. In my model only the uncertainty about the asset behind growth options matters. I believe that while bottom-line earnings do not convey much information about it (though they may if the growth option involves buying more assets in place like the ones the firm has), significant information about growth options is revealed at the earnings announcement, such as the information about investment and R&D activity in the financials, press-releases, etc.

I find that about 15-20% of the value effect, the idiosyncratic volatility discount, and their interaction with volatility and market-to-book is realized in the three days around the announcement date. I also find that while all effects are noticeably higher in the month before the announcement, indicating the predisclosure and information leakage, the idiosyncratic volatility discount is flipped in the month before the announcement.

I do not find any evidence of the risk shift after the announcement, but I do find a significant risk shift at the announcement. Somewhat unexpectedly, this risk shift is driven by HML beta, not the BVIX beta as my model would predict. The risk shift can explain about two-thirds of the relation between the value effect and volatility and the relation between the idiosyncratic volatility discount and market-to-book at the announcement. It can also explain about a third of the idiosyncratic volatility discount part concentrated at the announcement. It contributes nothing to explaining the announcement part of the value effect though.

3.2 Is the Idiosyncratic Volatility Discount Robust? Revisiting Bali and Cakici (2007)

In a recent paper, Bali and Cakici (2007) claim that the idiosyncratic volatility discount is not robust to reasonable changes in the research design. In particular, they argue that measuring idiosyncratic volatility from monthly data or looking at NYSE only firms eliminates the idiosyncratic volatility discount.

When I try to mimic the results in Bali and Cakici (2007), I find that they are contaminated by selection bias. When Bali and Cakici look at NYSE only firms, they define a NYSE firm using the current listing reported in the `hexcd` listing indicator from the

CRSP returns file. It creates a strong selection bias, because only good performers remain NYSE firms from the portfolio formation date till now. Bad performers, even if they were NYSE firms at the portfolio formation date, are likely to be subsequently downgraded to NASDAQ or even OTC, and therefore they do not make it into the Bali and Cakici "NYSE only" sample. On the other hand, good performers, even if they were NASDAQ at the portfolio formation date, are likely to make it into the "NYSE only" sample, because they may be upgraded to NYSE since then. This selection bias is evidently stronger for high idiosyncratic volatility firms, which are more likely to be upgraded or downgraded.

The natural way to avoid the selection bias is to look at the historical listing recorded in the `exchcd` indicator from the CRSP events file and use its value at the portfolio formation date to classify firms as NYSE firms. When I do it, I find that the idiosyncratic volatility discount in the NYSE only sample is actually larger than in the whole CRSP population.

I follow Bali and Cakici (2007) in measuring idiosyncratic volatility from monthly data. I define it as the standard deviation of the Fama-French model residuals, where the Fama-French model is fitted to monthly returns from 24 to 60 months ago (at least 24 valid observations are required for estimation). The monthly idiosyncratic volatility portfolios are rebalanced at the end of each month and held for one month afterwards. The daily idiosyncratic volatility measure in Bali and Cakici (2007) is the same as the one I use throughout the paper.

In Table 16 I look at the idiosyncratic volatility discount in the NYSE only sample. Panel A shows equal-weighted returns to the portfolios formed using the volatility from daily data, and Panel B shows equal-weighted returns to the portfolios formed using the volatility from monthly data. In the first two rows, I mimic Bali and Cakici (2007) by using `hexcd` from the CRSP returns file to classify firms as NYSE.

The raw returns are within 1 bp per month of what Bali and Cakici (2007) show in Table 2, Panel B, and in Table 4, Panel B. It convinces me that they were using the `hexcd` listing indicator, even though they are not explicit about it. In raw equal-weighted returns the idiosyncratic volatility discount turns into the idiosyncratic volatility premium of 25 bp (t-statistic 1.08) in Panel A and 51 bp (t-statistic 1.87) in Panel B. The respective Fama-French alphas show a small idiosyncratic volatility discount of 32 bp (t-statistic 2.67) and 3 bp (t-statistic 0.27).

When I matched Bali and Cakici (2007) in the top row of Table 16, I ignored delisting

returns as they apparently did. Adding the delisting returns back increases the idiosyncratic volatility discount by 3 bp per month, as shown in the third row.

In the fourth row, I use the value of the `exhcd` listing indicator from the CRSP events file at the portfolio formation date to classify firms as NYSE. The effect of removing the selection bias created by using `hexcd` is enormous - the alphas of the highest volatility quintiles go down by 55 bp per month, and the idiosyncratic volatility discount jumps up by the same amount. In the true NYSE only sample it is even higher than in the CRSP population at 85 bp per month, t-statistic 6.30, for the sorts on the daily volatility measure, and at 67 bp per month, t-statistic 4.87, for the sorts on the monthly measure.

Overall, Table 16 demonstrates that Bali and Cakici (2007) fail to find the idiosyncratic volatility discount because of the pitfalls in their research design. Once I eliminate the selection bias that contaminate their results, I find the idiosyncratic volatility discount alive and well exactly for the cases where they claimed to find the greatest evidence against it.

3.3 Testing the Johnson model

The Johnson model entertains the same basic idea that the riskiness of an option is inversely related to idiosyncratic volatility. It also predicts that returns are negatively related to idiosyncratic volatility and this relation is stronger for more option-like firms. The difference between the Johnson model and my model is that the option-like nature of the firm in the Johnson model stems from the limited liability of shareholders and it predicts that the pricing impact of idiosyncratic volatility increases with leverage. In empirical tests I also try using Ohlson's (1980) O-score as another measure of how option-like the firm is. While leverage and O-score are related, they capture two different dimensions of why the real option associated with risky debt may be close to being at the money: the firm can either be highly levered or financially distressed (or both).

On the empirical side, my model and the Johnson model tend to create different effects, since market-to-book is negatively correlated with leverage and O-score. In unreported results I show that leverage strongly and monotonically decreases along market-to-book quintiles, from 0.43 for extreme value firms to 0.15 for extreme growth firms. In the absence of any link between market-to-book and the idiosyncratic volatility discount the Johnson model would predict that idiosyncratic volatility is priced for value firms and not

priced for growth firms, as the former are more highly levered and have higher values of O-score. For the same reason, if my model was wrong, the Johnson model would predict higher value effect for low volatility firms.

In Table 17 I report the idiosyncratic volatility discount across the leverage (Panel A) and O-score (Panel B) quintiles. I measure leverage as debt over debt plus market value of equity, where debt is the sum of short-term debt (Compustat item #9) and long-term debt (Compustat item #34), and market value of equity is shares outstanding (Compustat item #25) times share price at the end of the fiscal year (Compustat item #199). I modify Ohlson's (1980) O-score as in Hillegeist et al. (2004) and define it as

$$\begin{aligned}
 Oscore = & -5.91 + 0.04 * TA + 0.08 * TL/TA + 0.01 * WC/TA - 0.01 * \\
 & CL/CA + 1.2 * NI/TA + 0.18 * FFO/TL + 0.01 * I[NI_{-1} + NI_0 < 0] \\
 & + 1.59 * I[TL > TA] - 1.1 * (NI_0 - NI_{-1})/(|NI_0| + |NI_{-1}|),
 \end{aligned} \tag{25}$$

where TA are total assets (Compustat item #6), TL are total liabilities (Compustat item #181), WC is working capital (Compustat item #179), CL and CA are current assets (Compustat item #4) and current liabilities (Compustat item #5), NI and FFO are net income (Compustat item #172) and funds from operations (Compustat item #170 plus Compustat item #14). When I use leverage and Ohlson's (1980) O-score, I further restrict my sample to industrial firms with SIC codes between 1 and 3999 and between 5000 and 5999. To compute the leverage and O-score I use current year book value and debt value for the firms with the fiscal year end in June or earlier or previous year book value for the firms with later fiscal year end, to ensure that the accounting information used to form the portfolios for asset-pricing tests is available before the date of portfolio formation.

The idiosyncratic volatility discount is measured as the abnormal value-weighted return to the portfolio long in the lowest volatility quintile and short in the highest volatility quintile. I measure the abnormal returns using the CAPM, the Fama-French model, and the two-factor ICAPM with BVIX. I use the data from August 1963 to December 2006 to estimate the CAPM and the Fama-French model, and the data from February 1986 to December 2006 to estimate the ICAPM. Estimating the CAPM and the Fama-French model using data from February 1986 to December 2006 does not change the tenor of the results. For the ICAPM, I also report the BVIX betas - if the interaction between leverage and idiosyncratic volatility drives the idiosyncratic volatility discount, it should

also reflect in the cross-section of the BVIX betas, which will increase with leverage along with the idiosyncratic volatility discount. As I mentioned in the first chapter, one can easily extend the Johnson model to predict that highly levered volatile firms have the lowest aggregate volatility risk, which explains why the idiosyncratic volatility discount in the Johnson model has to be stronger for highly levered firms.

In Table 17 I do not find any direct evidence in favor of the Johnson model. The alphas of all models do not follow any common pattern across the leverage quintiles or the O-score quintiles, and the difference in the idiosyncratic volatility discount between high leverage/O-score and low leverage/O-score is minuscule. However, if leverage had no impact on idiosyncratic volatility discount, the fact that market-to-book declines with leverage would cause us to find a strong negative relation between leverage and the idiosyncratic volatility discount (the same is true about O-score). Therefore, no pattern in alphas I find in Table 17 suggests that the Johnson model is true, but the effects it describes are not powerful enough to overturn the effects from my model that run in the other direction in cross-section.

I also notice that the BVIX betas decrease almost monotonically and quite significantly with leverage, as the negative relation between leverage and market-to-book implies. This pattern is quite different from what we observe for the alphas, and is open to two interpretations. First, it can be the case that the previous paragraph reads too much in the absence of any pattern in alphas and there is no relation between leverage and the idiosyncratic volatility discount. Second, the combination of high leverage and high idiosyncratic volatility can hedge against the dimension of aggregate volatility risk that is not captured well by the BVIX factor. Indeed, the volatility of distressed companies does not have to follow the same path as the volatility of the S&P 100 index. This hypothesis seems an attractive avenue for future research.

The double sorts do not seem a good framework for studying the effect of leverage-volatility (O-score-volatility) interaction controlling for the interaction between volatility and market-to-book. The most appropriate method seems to be the multiple cross-sectional regression similar to the ones in Table 3. I perform these regressions in Table 18.

In the first column of Table 18 I establish that the leverage discount, predicted by the Johnson model, exists and is independent of the idiosyncratic volatility discount. In

the second column the Johnson model seemingly fails, as the sign of the product of leverage and volatility is wrong and insignificant. Adding the leverage-volatility product also strengthens the effects of leverage and idiosyncratic volatility, while the Johnson model implies that the slopes on idiosyncratic volatility and leverage should be zero and positive, respectively, in the presence of the product.

I suspect that the failure of the Johnson model in the second column of Table 18 comes from the relation between leverage and market-to-book I discussed above. The results in the third column show that my intuition is correct, as once the interaction between market-to-book and volatility is controlled for, the product of leverage and volatility has the negative and significant sign (t-statistic -3.24), as predicted by the Johnson model. The presence of the leverage-volatility product makes the effect of leverage on returns significantly negative, while it is significantly positive in the regression with market-to-book - volatility product only (results not reported).

The magnitude of the leverage-volatility coefficient suggests that, controlling for the interaction between idiosyncratic volatility and market-to-book, the interaction between leverage and idiosyncratic volatility can explain the cross-sectional changes in the idiosyncratic volatility discount of about 60-65 bp per month. For comparison, the average magnitude of the discount implied by the first column is 76 bp, and the volatility - market-to-book product can explain the cross-sectional changes of about 180 bp per month. It implies that while, consistent with the Johnson model, the interaction between leverage and idiosyncratic volatility can explain a sizeable portion of the idiosyncratic volatility discount and its cross-section, the impact of the interaction between market-to-book and idiosyncratic volatility, predicted by my model, is much stronger.

In the last five columns of Table 18 I look at the tests of the Johnson model using the O-score. In column 4 I show that the O-score is negatively related to future returns, confirming the findings in Dichev (1998) for the updated O-score definition and for a longer period of time. I also find in column 5 that the O-score effect is totally independent from the leverage effect documented in column 1. It is somewhat surprising, since both variables are used to measure the same thing - how close the option created by risky debt is to being in the money. However, as I mentioned above, leverage and O-score measure different aspects of at-the-moneyness of the real option associated with existence of debt.

In the sixth column I drop leverage from the regression and include the product of

O-score and idiosyncratic volatility. Its coefficient has the right sign, but is insignificant with t-statistic of -1.21. The inclusion of the product of O-score and volatility makes the O-score insignificant and cuts the magnitude and significance of idiosyncratic volatility, which is consistent with the Johnson model. When I add the product of volatility and market-to-book in the seventh column, the O-score - volatility product becomes marginally significant (t-statistic -1.77). Its magnitude suggests that, controlling for the market-to-book - volatility relation, the idiosyncratic volatility discount changes by about 37 bp per month (a half of its average magnitude) as one goes from the lowest to the highest O-score quintile. On the other hand, going from the lowest to the highest market-to-book quintile creates the 165 bp variation in the idiosyncratic volatility discount (compared to 126 bp implied by Table 3). It implies that, first, market-to-book captures a much more important cross-sectional dimension of the idiosyncratic volatility discount, and second, that having both products in one regression strengthens both.

In the last column of Table 18 I run the horse race between leverage-volatility and O-score-volatility products. In the horse race they interfere with each other, again consistent with the Johnson model, and the leverage-volatility product wins, since both of them retain the negative sign, but only the leverage-volatility product is marginally significant (t-statistic -2.31).

The bottom line from this section is that while the Johnson model seems to contribute to explaining the idiosyncratic volatility discount, it is unable to explain the whole of it. The interaction between idiosyncratic volatility and market-to-book captured by my model turns out to be much more important empirically. I also find that controlling for the product of O-score and idiosyncratic volatility, as the Johnson model suggests, explains the O-score effect on future returns, documented in Dichev (1998).

3.4 Investment and the Idiosyncratic Volatility Discount

Several recent studies (e.g., Anderson and Garcia-Feijoo, 2006, and Titman, Wei, and Xie, 2004) empirically establish the investment anomaly, i.e. the strong negative relation between investment and future returns. The rational explanation, provided in Xing (2007) and Carlson, Fisher, and Giammarino (2004), leans on the Q-theory and has it that the heavily investing firms do so because they have abundant low-risk investment opportuni-

ties. An example of successful application of the investment factor is Lyandres, Sun, and Zhang (2007), discussed in the second chapter.

On the surface it seems that the negative relation between investment and expected returns contradicts the assumption of my model that growth options are less risky than assets in place. If that is the case, investment should mean foregoing valuable hedges by exercising growth options and thereby increasing expected returns. However, this logic is only true in time-series - after investing heavily, the firm will become riskier than it used to be. In cross-section heavily investing firms can still have much more growth options and the associated hedges than firms with low investment, even after they exercise some. In other words, investment may just be the alternative proxy for the amount of low-risk growth options.

If investment in asset-pricing tests substitutes for market-to-book, it is quite surprising that the investment factor and the BVIX factor are unrelated. From my model I would predict that, first, the idiosyncratic volatility discount increases with investment, second, that the investment anomaly increases with idiosyncratic volatility, and third, that these patterns are explained by BVIX, which implies that BVIX should partly explain the average magnitude of the investment anomaly. In this section I test all predictions and examine more closely the relation between investment and the investment anomaly, on the one hand, and idiosyncratic volatility, the idiosyncratic volatility discount, and aggregate volatility risk, on the other.

In Table 19 I look at the investment anomaly across idiosyncratic volatility quintiles. I define the investment anomaly as the value-weighted abnormal return differential between low investment and high investment firms. I define investment in three alternative ways - in Panel A as the change in CAPEX (which is actually investment growth, as in Xing, 2007, and Anderson and Garcia-Feijoo, 2006), in Panel B as the change in gross PPE over assets, and in Panel C as the change in gross PPE and inventories over assets (as in Lyandres, Sun, and Zhang, 2007). The abnormal returns are from the CAPM, the Fama-French model, and the two-factor ICAPM with BVIX. I also report the BVIX betas from the ICAPM. The sample period is from February 1986 to December 2006. Extending the sample period where possible does not change the results.

I do not find any significant pattern in the alphas or BVIX betas in Panel A, where I define investment as the growth in CAPEX. From Panel A, it seems that the investment

anomaly is not related to idiosyncratic volatility and aggregate volatility risk. However, in Panels B and C, which look at investment over assets as a measure of high or low investment, I do find some economically large and mostly marginally significant difference in the investment anomaly between high and low volatility firms. The difference in abnormal returns to the investment arbitrage portfolio in the lowest volatility quintile and the highest volatility quintile, according to Panel C, ranges between 74 bp and 109 bp, and the t-statistics range between 1.8 and 2.4. The BVIX factor seems to contribute to explaining the differential - the respective difference in the BVIX betas is 0.4 in Panel B (t-statistic 3.52) and 0.3 in Panel C (t-statistic 2.59). In fact, controlling for aggregate volatility risk reduces the differential in the investment anomaly from 81 bp, t-statistic 1.72, and 109 bp, t-statistic 2.44, to 42 bp, t-statistic 0.99, and 81 bp, t-statistic 1.92, in Panel B and C, respectively.

However, while the BVIX factor is helpful in explaining the cross-section of the investment anomaly, the only significant BVIX betas of the investment arbitrage portfolios in all volatility quintiles are negative, and they occur for the lowest volatility firms. All other BVIX betas in Table 19 are mostly positive, but never close to being significant. That explains how the investment factor comes to be uncorrelated with the BVIX factor, even though BVIX contributes to explaining the investment anomaly.

In Table 20 I turn to the relation between investment and the idiosyncratic volatility discount. By construction, the rightmost column measuring the difference in the idiosyncratic volatility discount across the investment quintiles is the same as the rightmost column in Table 19, so the comments in the previous paragraphs apply to Table 20 as well. In particular, the idiosyncratic volatility discount is unrelated to CAPEX growth, is somewhat related to investment in PPE over assets, at least according to BVIX betas, and is clearly related to investment in PPE and inventories over assets.

The major difference is in the inside columns. First, I notice that the idiosyncratic volatility discount is only significant for high volatility firms. It is partly the power issue coming from slicing the idiosyncratic volatility discount too thin, but since the power should be the lowest for high volatility firms, this piece of evidence confirms that empirically investment just stands for a growth options measure in my model. Second, the idiosyncratic volatility discount and the BVIX betas are now always positive and significant, as expected, and increase almost monotonically from bottom investment quintile to

top investment quintile, the only large splash being the lowest investment growth quintile in Panel A, which is the primary reason I do not find any relation between investment and the idiosyncratic volatility discount there. Overall, while the rightmost column of Table 20 is the same as the one in Table 19, there is more evidence in Table 20 to suggest that the idiosyncratic volatility discount is related to investment.

The overall conclusion from the section is that in double sorts on investment and idiosyncratic volatility investment seems to substitute, albeit imperfectly, for market-to-book. All the predictions of my model go through with investment as an empirical proxy for growth options, but the relations are somewhat weaker compared to the main case with market-to-book as the growth options proxy. The only difference is that the investment arbitrage portfolio in the low volatility quintile has the significantly negative BVIX beta, while the value-growth arbitrage portfolio in the low volatility quintile has the zero BVIX beta. It explains why BVIX can explain a significant part of the value effect, but, on average, BVIX seems unrelated to the investment anomaly.

3.5 BVIX Robustness

This section explores the robustness of the BVIX factor performance to different ways of forming the factor portfolio. The baseline case I use throughout the thesis is measure the return sensitivity to VIX changes using daily data from the previous month and hold the VIX sensitivity portfolios for one month only. BVIX is then the value-weighted return differential between the most negative return sensitivity portfolio and the most positive return sensitivity portfolio.

There are several concerns about this procedure. First, the one-month holding period can be too short and the returns could potentially be influenced by microstructure issues. It either throws in noise or a liquidity component in the BVIX factor, which makes finding meaningful results with BVIX harder - the anomalies it works on tend to become stronger if one controls for liquidity. However, in this section I still check how BVIX works if hold the return sensitivity portfolios for twelve months, or eleven months skipping the month after the formation. Because I still sort stocks each month, holding the return sensitivity for twelve months after means that in each month the return to the VIX sensitivity portfolio is the simple average of returns to the twelve portfolios formed one, two, etc. up to twelve

months ago. I expect that BVIX will perform better as I make the holding period longer to the extent I wipe out the noise and worse to the extent the sensitivities become stale and less relevant.

Second, one can be concerned that a month is too short period to estimate the sensitivity precisely. Again, it works against finding anything significant with the BVIX formed using the sensitivities from the previous month only if it makes the estimated sensitivities noisy. However, I also try estimating the sensitivities from the previous twelve months of daily data and holding the portfolio for the next twelve months. Again, I rebalance the portfolios monthly, therefore in each month the return to the VIX sensitivity portfolio is the simple average of returns to the twelve portfolios formed one, two, etc. up to twelve months ago.

I refrain from trying to estimate the sensitivities from monthly data because at the monthly frequency the VIX change is a much poorer proxy for the change in the market volatility expectations than at the daily frequency, and trying to capture the change in market expectations by a time-series model is likely to do more harm than the gain from weaker microstructure issues in the monthly data.

Table 21 presents the results of the robustness checks. In Panel A I test the performance of different versions of BVIX against the four arbitrage portfolios from the first chapter, which capture the idiosyncratic volatility discount, its relation to market-to-book, and the value effect for the most volatile firms. In Panel B I test the robustness of BVIX as the explanation of the small growth anomaly, which is represented by the smallest and the second smallest growth portfolios (both equal-weighted and value-weighted) from the Fama and French (1992) size - book-to-market sorts. In Panel C I test the performance of BVIX versions against the new issues puzzle - the IPO portfolio, the SEO portfolio, and the cumulative issuance arbitrage portfolio I worked with in the second chapter.

In the first two columns I have the ICAPM alpha and the BVIX beta with the usual definition of the BVIX factors. The results just repeat the ones elsewhere in the thesis. In the second pair of columns I use the BVIX formed on the previous month return sensitivities and held for twelve months after. The BVIX betas magnitudes are not comparable across the columns, because they depend on the return premium each version of BVIX earns. What is comparable, though, are the alphas, their t-statistics, and the t-statistics of the BVIX betas. Judging from those, the BVIX with the annual holding period performs

slightly better on the idiosyncratic volatility discount than the baseline BVIX, slightly worse on the value effect, and about the same on the small growth anomaly and the new issues puzzle.

In the third pair of columns I skip the month after forming the return sensitivity portfolios that make up the BVIX factor. The resulting version of the BVIX factor performs slightly worse on all anomalies except for the new issues puzzle and I find some marginally significant alphas here and there. However, the alphas magnitude is very close to the baseline case and all main results in my thesis qualitatively hold with this new version of BVIX.

In the last pair of columns I use the BVIX factor long and short in the portfolios formed on the previous twelve month sensitivities and held for twelve months after. This version of the BVIX factor performs slightly worse on all anomalies, but the difference in the alphas, as before, is only a few basis points per month, even though a couple of the alphas come to the brink of significance.

Overall, the results in this section are extremely comforting in the sense that the BVIX factor performance turns out to be extremely robust to all reasonable modifications of the portfolio formation procedure. The explanatory power of BVIX is very likely to stem from the economics behind it, not any sort of fortunate glitch in the data.

3.6 Behavioral Stories

Several recent empirical papers find evidence consistent with the behavioral explanation of the idiosyncratic volatility discount. The behavioral story is based on the Miller (1977) argument that under short sale constraints firms with greater divergence of opinion about their value will be more overpriced as a result of the winner's curse. Consistent with this idea, Nagel (2004) and Boehme, Danielsen, Kumar, and Sorescu (2006) find that the idiosyncratic volatility discount is much stronger for the firms with low institutional ownership and high short interest.

Gompers and Metrick (2001) find that institutional ownership is negatively related to market-to-book, and D'Avolio (2002) estimates that the costs of shorting are higher for growth stocks. It means that limits to arbitrage are likely to be higher for growth stocks, and the relation between them and the idiosyncratic volatility discount can therefore drive

my cross-sectional results.

A somewhat different behavioral story, yet unexplored in the literature, is that in my setup market-to-book can be just another measure of overpricing, and my cross-sectional results arise only because double sorts always create more variation in returns than single sorts. If it is the case, I would expect the interaction of volatility and market-to-book to be stronger for the stocks with higher limits to arbitrage.

Due to availability of the institutional ownership data, the sample period in this subsection starts in April 1980. I also restrict my sample to the stocks above the 20th NYSE/AMEX size percentile, since the other stocks usually have zero institutional ownership. I follow Nagel (2004) in looking at residual institutional ownership, which is orthogonalized to size (see equation (19)).

I do not have access to the short interest data and use the estimated probability that the stock is on special. The exact formula is given in (20) and (21) (see Section 3.1). It uses the coefficients estimated by D'Avolio (2002) for a short 18-month sample of short sale data. Ali and Trombley (2006) use the same formula to estimate the probability to be on special for the intersection of Compustat, CRSP, and Thompson Financial populations. They show that it is closely tied to other short sale constraint measures in different periods.

Panel A of Table 22 looks at the interaction between the idiosyncratic volatility discount and the residual institutional ownership in the firm-level cross-sectional regressions. In the first three columns I verify that the previously documented phenomena are present in my sample. I start with regressing returns on the current month beta, size, market-to-book, and idiosyncratic volatility for firms with non-missing residual institutional ownership only. Then I add the residual institutional ownership and its product with idiosyncratic volatility. I subtract 100 from the percentage ranking of institutional ownership so that the slope of the idiosyncratic volatility in the presence of its product with institutional ownership measured the idiosyncratic volatility discount for the highest, not lowest, institutional ownership firms. All independent variables are percentage ranks, and the sample period is from April 1980 to December 2006.

In the first column I find that in my sample the idiosyncratic volatility discount is large and significant with t-statistic 3.93. The second column of Panel A I confirm the return premium earned by the stocks with the highest residual institutional ownership (see Chen, Hong, and Stein, 2002, and Nagel, 2004). Controlling for the premium does not reduce

the estimated magnitude of the idiosyncratic volatility discount. In the third column I find that the product of idiosyncratic volatility and residual institutional ownership is significantly positive with the t-statistic of 5.77 and the idiosyncratic volatility discount becomes insignificant in its presence. It confirms another result in Nagel (2004) that the idiosyncratic volatility discount is limited to the lowest institutional ownership stocks.

In the fourth column of Panel A I show that the dependence of the idiosyncratic volatility discount on institutional ownership is distinct from the effect in Nagel (2004). I include in the regression both the product of volatility and market-to-book and the product of volatility and residual institutional ownership. Both products are highly significant and their magnitude diminishes only slightly compared to the cases when they are used alone. I conclude that while there is supporting evidence for the behavioral story, the effect predicted by my model is clearly distinct from it.

In the fifth column I add the product of idiosyncratic volatility, market-to-book, and institutional ownership. The alternative behavioral story I develop in this subsection implies that it should have a positive sign and drive away the product of idiosyncratic volatility and market-to-book. I find that the interaction of volatility and market-to-book matters significantly more for low institutional ownership firms, consistent with the behavioral story. The interaction of volatility and market-to-book for the highest institutional ownership stocks is only a half of its value in column four and its t-statistic is -1.87. However, for the firms with institutional ownership above the 10th percentile the product of idiosyncratic volatility and market-to-book restores significance.

In Panel B I repeat the analysis for the probability to be on special, which is my proxy for short sale constraints. In the first column I find that the idiosyncratic volatility discount is alive and well in the sample with non-missing probability to be on special. In the second column I confirm the results of Asquith, Pataak, and Ritter (2005) that higher short sale costs imply lower future returns, as the Miller (1977) model would imply. In the third column of Panel B I find that the product between idiosyncratic volatility and the probability to be on special is negative and significant with t-statistic -4.51. It means that the strength of the idiosyncratic volatility discount strongly depends on the level of short sale constraints, as Boehme et al. (2006) show. I also find that the idiosyncratic volatility discount is zero for the lowest short sale constraints firms.

In column four of Panel B I find that the interaction of volatility and market-to-book

predicted by my model is distinct from the effect in Boehme et al. (2006). The product of idiosyncratic volatility and market-to-book does not change its magnitude and significance in the presence of the product of idiosyncratic volatility and the probability to be on special.

In the last column of Panel B I find that the product of volatility, market-to-book, and the probability to be on special makes the two other products insignificant, and it is insignificant itself. It suggests that this product should not probably be there and it only spoils the model because it is correlated with both the product of volatility and market-to-book and the product of volatility and the probability to be on special.

A possible problem with the regression in the last column is that the probability to be on special includes the glamour dummy and is correlated with market-to-book by construction. In untabulated results I try calculating the probability to be on special without the glamour dummy. I find that the regression in the last column gives the same result, with the significance of the volatility and market-to-book product slightly increased.

Overall, the results in Table 22 are inconclusive. While the results in my paper clearly are not subsumed by the Nagel (2004) or Boehme et al. (2006) stories, the interaction of volatility and market-to-book does not explain the evidence in Nagel (2004) and Boehme et al. (2006) either. Moreover, its strength depends on institutional ownership. To understand better the nature of what I label "behavioral effects" in the cross-sectional regressions, I run covariance-based tests in Table 23.

In Table 23 I measure the idiosyncratic volatility discount in each limits-to-arbitrage quintile using the value-weighted abnormal returns from three asset-pricing models - the CAPM, the Fama-French model, and the ICAPM with BVIX. The behavioral story behind the idiosyncratic volatility discount and Table 22 suggest that the idiosyncratic volatility discount should be stronger for high limits-to-arbitrage firms. My model, on the other hand, predicts that all cross-sectional variation in the idiosyncratic volatility discount should be related to risk.

Both Panel A (residual institutional ownership) and Panel B (probability to be on special) reach the same conclusion. Even the CAPM alphas do not confirm that the idiosyncratic volatility discount is reliably different between the quintiles with the lowest and the highest limits to arbitrage. While the difference in the CAPM alphas is large (about 80 and 70 bp), it is significant only at the 10% level. Using the Fama-French alphas instead reduces the difference to about 30 bp and 10 bp with minuscule t-statistics. Also, both the

Fama-French model and the ICAPM can explain the idiosyncratic volatility discount in all limits-to-arbitrage quintiles, except, probably, the lowest institutional ownership quintile.

The fact that the BVIX betas are flat across the limits-to-arbitrage quintiles is consistent with Table 22. It means, as shown by columns four in Table 22, that the behavioral effects and the effects predicted by my model are unrelated.

Overall, Table 23 questions the reliability of the behavioral effects. The difference between Table 22 and Table 23 can come from two sources. First, it is possible that firm characteristics are poor risk controls. Second, it is possible that the behavioral effects in the firm-level regressions are caused by some outliers, which are muted in portfolios. Whichever of the two is true, the absence of the behavioral effects in the portfolios alphas seems to imply that they are not real.

Nagel (2004) also performs five-by-five sorts on idiosyncratic volatility and institutional ownership. He finds that the idiosyncratic volatility discount, measured as the Fama-French alpha, is reliably different for low and high institutional ownership firms. Nagel (2004) uses the data from September 1980 to September 2003, while I use the data from February 1986 to December 2006. In unreported analysis I find the difference in our results is driven by the period from September 1980 to January 1986. That is, the idiosyncratic volatility discount depends on institutional ownership only in the early 1980s.

Boehme et al. (2006) do find that the idiosyncratic volatility discount depends on the short sale constraint in the portfolio sorts. However, their research designs is too different from mine to allow simple comparison. First, they use direct data on short interest from NYSE and NASDAQ to sort on short sale constraints. Second, they augment the Fama-French model with the momentum factor to compute the alphas. Third, they perform four-by-twenty sorts. Without the data on short interest it is difficult to assess what drives the difference in our results.

3.7 The Three Idiosyncratic Volatility Effects and Earnings Announcements

3.7.1 Announcement Returns

The behavioral literature often argues that mispricing is corrected at earnings announcements. For example, the evidence that a significant part of underperformance is realized

at the earnings announcement is usually interpreted as the evidence that the underperformance reflects overoptimism, and the announcement effect measures the disappointment.

My model offers a risk-based reason why the value effect and the idiosyncratic volatility discount can be concentrated at earnings announcements. In my model, higher idiosyncratic volatility at earnings announcements (as the market digests the information) and lower idiosyncratic volatility afterwards (because some uncertainty is resolved) implies that the risk of growth, high volatility, and especially high idiosyncratic volatility firms decreases at earnings announcements and increases afterwards. It implies that the idiosyncratic volatility discount and the value effect should be stronger at earnings announcements and the betas of the respective arbitrage portfolios should sharply increase at the earnings announcements. After the announcements the betas should decrease compared to what they were before the announcement.

In my model, idiosyncratic volatility reduces risk through growth options, which means that only the uncertainty about the underlying asset behind growth options matters. In general, accounting earnings should measure current cash flows and ignore the changes in firm value that come from revaluing the growth options. However, the financials that are disclosed at earnings announcements contain a lot of valuable information about growth options such as investments and R&D expenses. The management also communicates to the market its perceptions of the firm's prospects in the accompanying press-release. Moreover, in many cases the value of growth options is closely related to the value of assets in place - for example, the profitability of existing stores is a good indicator of the value of the option to open more stores. Therefore, while the value of growth options is certainly not disclosed at earnings announcements, important information about their value is revealed.

In this subsection, I start the analysis of the idiosyncratic volatility discount and the value effect at earnings announcements with looking at earnings announcement returns. To my knowledge, the only evidence documented in the literature is more negative announcement returns for growth firms (see, e.g., La Porta et al., 1997). My model makes two additional predictions. First, I expect the idiosyncratic volatility discount to be concentrated around earnings announcement. Second, I expect the announcement part of the value effect to be larger for high volatility firms, and the announcement part of the

idiosyncratic volatility discount to be larger for growth firms⁹.

In Panel A of Table 24, I look at the value-weighted announcement returns to the 25 idiosyncratic volatility - market-to-book portfolios. I use the earnings announcement dates from Compustat and measure the announcement return as the cumulated return for the three trading dates around the earnings announcement. I divide the announcement returns by 3 to make them comparable to the monthly raw returns I report in Panel B. The sample period is from July 1971, when Compustat starts reporting the announcement dates, to December 2006. The results are also robust to using equal-weighted instead of value-weighted returns and looking at the second earnings announcement after portfolio formation.

Earnings announcements happen only once per quarter, so I have to track each portfolio for a quarter rather than a month, but I still do the monthly rebalancing. Each month I average the announcement returns to the portfolios formed one, two, and three months ago and report the average in Panel A. Clearly, the portfolio formed one (two, three) month ago contributes the returns from the announcements that happened in the first (second, third) month after the portfolio formation. To make the announcement returns in Panel A and raw returns in Panel B comparable I follow the same strategy in Panel B. The returns to the idiosyncratic volatility portfolios reported there are the average raw returns to the portfolios formed one, two, and three months ago.

Table 24 shows that, consistent with my model, the difference in the announcement returns between high and low volatility firms is significant only in the highest market-to-book quintile. Consistent with what my model predicts, the idiosyncratic volatility discount at the earnings announcement monotonically increases with market-to-book, starting with 2 bp, t-statistic 0.31, for value firms and ending up with 21 bp, t-statistic 3.24, for growth firms. The difference of 19 bp is statistically significant (t-statistic 2.22). Also consistent with my model, the value effect at the announcement starts with 11 bp, t-statistic 2.26, and increases almost monotonically to 30 bp, t-statistic 4.1. I notice the sharp spike in the announcement portion of the value effect - the second highest value in the second highest volatility quintile is only 12 bp. The only significantly negative announcement re-

⁹Dimitrov, Jain, and Tice (2007) find possibly related evidence that the underperformance of the firms with high level of analyst disagreement is concentrated at earnings announcements, but do not discuss any cross-sectional pattern of this effect

turn accrues to the highest volatility and highest market-to-book portfolio, which is again consistent with my model.

The pattern in announcement returns follows closely a similar pattern in raw returns (Panel B), where the idiosyncratic volatility discount also increases with market-to-book is limited to the two highest market-to-book quintiles, and the value effect increases with idiosyncratic volatility. The comparison of the raw and announcement returns suggests that 15-20% of the three idiosyncratic volatility effects are realized in the three days around earnings announcement, which are only 5% of the trading days in a quarter.

La Porta et al. (1997) report similar evidence for the value effect. They find that 20% of the value effect is realized in the three days around the earnings announcements and interpret this result in favor of the mispricing explanation of the value effect. Table 24, however, makes several important contributions beyond just confirming the La Porta et al. (1997) result in a more recent sample. First, it shows that the La Porta et al. result is driven by the firms in the highest volatility quintile. La Porta et al. (1997) show that their result is weaker, but still significant for the firms above the median NYSE size. However, idiosyncratic volatility turns out to be a better proxy for the difference of announcement returns between value and growth firms. The effect I capture in Table 24 is likely to be behind the relation of the difference in announcement returns and size La Porta et al. (1997) document.

Second, I show that a significant part of the idiosyncratic volatility discount is realized around earnings announcements and this result is driven by the growth firms. To sum it up, for all three idiosyncratic volatility effects a significant part is realized around earnings announcements. Most importantly, my model provides a potential risk-based explanation of this fact, linking the announcement returns to the changes in risk. Testing the risk-based explanation is the subject of the next subsection.

Skinner and Sloan (2002) argue that looking at the short window around earnings announcements misses the bigger part of the investor disappointment in growth stocks. The disappointing news can come in the form of predisclosure before the earnings announcement, missing the usual announcement date, rumors, etc. They show that while 15% of the value effect is realized in the three days around the earnings announcement, 85% is realized in the second half of the period between the consecutive earnings announcements.

In Panels C and D I check if a similar picture exists for the three idiosyncratic volatility

effects. In Panel C I report the returns to the 25 idiosyncratic volatility portfolios in the 30 calendar days prior to an earnings announcement, ending in the second trading day before the announcement. In Panel D I do the same for the 30 calendar days after the announcement, starting with the second trading day after the announcement. As in the previous panels, the idiosyncratic volatility portfolios are rebalanced monthly, but tracked for the next quarter. I also tried partitioning the interval between the consecutive announcements in roughly equal halves, as in Skinner and Sloan (2002), and it left the results roughly the same.

The returns pattern in Panel C is quite different from what the behavioral stories would predict. First, I find that the idiosyncratic volatility discount is significantly negative in the month before the earnings announcement. In terms of disappointment, it means that investors are disappointed with low volatility, rather than high volatility, firms, as the information leakage before the earnings announcement occurs. This is in sharp contrast to the behavioral story.

Second, I find that the value effect in the month before the announcement is only 50% stronger than average. The value effect does not disappear in the month after the announcement, but then it is two times less than before the announcement, and is concentrated in the highest volatility quintile. Contrary to that, Skinner and Sloan (2002) argue that the value effect is absent after the announcement. Also, the difference in the value effect between high and low volatility firms in the month before the announcement (1.67%, t-statistic 3.28) is also quite comparable to its average value (1.23%, t-statistic 3.78) and its value after the announcement (0.96%, t-statistic 1.89).

To sum up the findings of the subsection, I do find that 15 to 20% of the value effect, the idiosyncratic volatility discount, and their relation to volatility and market-to-book is realized in the three days around earnings announcement. However, I find that the result of Skinner and Sloan (2002) that the vast majority of the value premium is realized in the second half of the between-announcement period is more moderate in the longer sample. I also find that in the month before the earnings announcement the idiosyncratic volatility discount turns into the idiosyncratic volatility premium, rejecting the behavioral story that investors are disappointed in high volatility firms as the information leaks before the announcement.

3.7.2 Betas and the Announcement Effects

Behavioral stories claim that growth, high volatility and especially high volatility growth firms are overpriced. It means more negative earnings announcement returns for all those types of firms, because investors are disappointed by the earnings announcements of overpriced firms. While the prediction is the same as in my model, the driving force is different. My model predicts the more negative earnings announcement returns to growth and high volatility firms because of the change in current or expected risk. The behavioral stories predict the same because of the change in expected cash flows and/or the difference between realized and expected cash flows.

To differentiate between my model and the behavioral stories I first need to show that either the betas of growth, high volatility, and high volatility growth firms increase after earnings announcements, or that the betas decrease strongly precisely at the announcement date.

Table 25 looks at the betas changes around earnings announcements. I estimate the market betas and the BVIX betas by fitting the ICAPM to daily firm-by-firm data and I do the same with the Fama-French model to estimate the SMB and HML betas. Pre-announcement betas are estimated using the data from 30 calendar dates preceding the announcement, ending two trading dates before it. Post-announcement betas are estimated using the data from 30 calendar dates following the announcement, starting two trading dates after it. The beta change is the difference between pre-announcement and post-announcement betas. The sample period is from February 1986 to December 2006 because of the BVIX factor availability, but including the data up to July 1971 does not change the conclusions I draw about other betas.

Since earnings announcements happen once per quarter, I form the idiosyncratic volatility portfolios each month, but follow them for a quarter afterwards. Analogous to the previous section, for each month the beta change for a volatility portfolio is the average of the changes in the betas for the volatility portfolios formed two, three, and four months ago that occurred in this month.

I do not use the change in betas for the portfolio formed one month ago, because for this portfolio pre-announcement betas would be estimated using the data from the portfolio formation period. The risk story implies that stocks with high volatility have lower future returns, because they have lower future betas. So, if I measure pre-announcement betas in

the portfolio formation month, the risk story would imply that they should decline in the first month after the portfolio formation. But the resolution of idiosyncratic risk around earnings announcements implies just the opposite, suggesting that the announcement in the first month after the portfolio formation should be excluded from the study of the betas changes around earnings announcements.

In Table 25 I do not find any significant changes in any betas. The significant values are scattered across the panels quite erratically and do not follow any pattern, which appears to imply that their occasional significance is merely a statistical phenomenon. I conclude that the betas of arbitrage portfolios that try to exploit the value effect, the idiosyncratic volatility discount, and their dependance on volatility and market-to-book do not change significantly around earnings announcements, and the risk-shift story cannot explain why these effects are concentrated at the earnings announcement.

In Table 26, I look at the betas in the three days around the announcement and compare them with the betas for the whole period. The betas are computed from portfolio-level daily regressions (ICAPM in the case of the market and BVIX betas, Fama-French in the case of the SMB and HML betas), which use the whole sample period from February 1986 to December 2006. To compute the portfolio returns, each day within each of the 25 market-to-book - volatility portfolios I take the weighted average of the announcement returns. I do not distinguish here between the returns in the day of the announcement or the days before and after. That is, the weighted average can include the return in the announcement day to some stocks and the returns in the days around the announcement for the other stocks in the portfolio. The idiosyncratic volatility portfolios are rebalanced each month, but tracked for three months afterwards¹⁰.

In Panel A I look at the value-growth arbitrage portfolio. I do not find any discernable pattern in the BVIX and SMB betas. I do find that the market betas tend to decline

¹⁰In Table 26 the High minus Low and the Value minus Growth alphas and betas are not the same as the difference of the numbers in the respective cells. It occurs because for some dates the daily returns to some of the 25 volatility - market-to-book portfolios are missing, i.e. none of the firms in this portfolio announced earnings on this date or in one trading day before and after. The alphas and betas of the individual portfolios are computed using individual samples, and the differences in alphas and betas are computed using the common sample. Using the common sample to compute the alphas and betas of the individual portfolios does not change the results.

by about 0.2 at the announcement, but the market beta of the portfolio that exploits the difference in the value effect between the highest and the lowest volatility quintiles increases by 0.2 at the announcement. Therefore, accounting for the market risk can partly explain why the difference in the value effect between high and low volatility firms is so large at the announcement, but it also makes harder to explain why the value effect is concentrated at the announcement.

The strongest evidence about the risk shift at the announcement date comes from HML betas. The HML beta of the value-growth arbitrage portfolio increases at the announcement by 0.44 for high volatility firms and decreases by 0.6 for low volatility firms. It can partly explain why the value effect is so strong at the announcement in the highest volatility quintile, but cannot explain why it is still positive for low volatility firms. The HML beta of the portfolio that tries to exploit the difference in the value effect between high and low volatility firms takes an amazing jump of 1.17 at the announcement, contributing a lot to the explanation of why the value effect at the announcement is so much different for high and low volatility firms.

The back-of-envelope calculations show that the risk shift at the announcement is enough to explain about two-thirds of the announcement effect for the difference in the value effect between high and low volatility firms. Both the market factor and the HML factor earn about 3 bp per day, or 9 bp per a three-day period. If the market beta goes up by 0.2 and the HML beta increases by 1.2, the implied change in the risk premium is about 13 bp, which is two thirds of the 19 bp announcement effect. The average announcement effect for the value-growth arbitrage portfolio is much harder to explain, because the beta shifts are much smaller and often go in the wrong direction.

In Panel B of Table 26 I look at the beta shifts for the idiosyncratic volatility discount. Because the portfolio exploiting the difference in the idiosyncratic volatility discount between value and growth firms is the same as the one exploiting the difference in the value effect between high and low volatility firms, all the comments above about explaining the cross-section of the value effect apply to explaining the cross-section of the idiosyncratic volatility discount.

As for the average level of the idiosyncratic volatility discount, Panel B shows that all betas of the high volatility minus low volatility portfolio, except for the BVIX betas, tend to increase at the earnings announcement. The market beta increases by about 0.15,

the SMB beta increases by about 0.25, the BVIX beta decreases by about 0.15, and the HML beta decreases by 0.36 for value firms and increases by 0.68 for growth firms. The announcement effect for the low-minus-high arbitrage portfolio in Table 24 is significant only for growth firms, where it is 21 bp. If one assumes conservatively from looking at the respective betas in Table 26 that the changes in the market, SMB, and BVIX betas cancel out and the HML beta increases by 0.7, the risk premium would increase by about 6.5 bp, which is about 30% of the announcement effect. It is clearly better that what I had for the value effect, where the beta changes at the announcement went mostly in the wrong direction.

The overall conclusion of the section is that the behavior of the idiosyncratic volatility discount and the value effect around earnings announcements is quite different. While 15-20% of both is realized at the announcement date, I do not find any concentration of the idiosyncratic volatility discount in the month before the announcement, where most disclosure happens. The idiosyncratic volatility discount is non-existent in the pre-announcement month and strong afterwards. Just the opposite is true for the value effect - it is notably stronger in the month before the announcement, and weaker, though still alive, in the month after the announcement.

I do not find any beta shift after the announcement that would help to explain the announcement effects. I do find quite large beta shifts at the announcement date that can potentially explain about two-thirds of the the difference in the idiosyncratic volatility discount between value and growth firms and the difference in the value effect between high and low volatility firms at the earnings announcement. The beta shifts at the announcement are no good at explaining the average value effect at the announcement, but they can explain about a third of the idiosyncratic volatility discount at the announcement. The only problem is that the announcement effects are primarily explained by the shift in the HML beta, not the BVIX beta, as my model would predict. All-in-all, the pattern in announcement returns is consistent with my model and at the earnings announcement date the idiosyncratic volatility effects captured by my model can be at least partly traced back to the change in risk. The value effect itself, which is not a part of my model, is much harder to link to any risk shift at the announcement.

3.8 Conclusion

In this chapter I perform a number of robustness checks and tests of alternative stories. I find that the evidence in Bali and Cakici (2007) that the idiosyncratic volatility discount is not robust is driven primarily by the selection bias caused by their use of the current listing instead of the listing at the portfolio formation date.

I find that the interaction between volatility and market-to-book in my model is not proxying for the interaction between leverage and volatility from the Johnson (2004) model. In fact, these two effects go against each other, and the Johnson (2004) effect is only visible once I control for mine.

I also find that investment can substitute quite well for market-to-book in cross-sectional tests - the idiosyncratic volatility discount and the respective BVIX betas are related to it. The investment anomaly is also related to volatility and BVIX betas pick it up. The only difference from the value effect is that the investment anomaly on average is unrelated to aggregate volatility risk and is negatively related to it in the absence of idiosyncratic volatility.

I try several alternative ways of forming the BVIX factor, changing the portfolio formation period and the portfolio holding period, and find that its performance as the explanation of all anomalies in my thesis is remarkably stable with respect to those changes.

I test the competing behavioral explanations of the idiosyncratic volatility discount and find that they do not subsume my results. There is some evidence that the idiosyncratic volatility discount and the interaction of volatility and market-to-book are stronger if limits to arbitrage are higher. However, in covariance-based tests the link between the idiosyncratic volatility discount and limits to arbitrage seems to be explained by the three Fama-French risk factors, which contradicts the behavioral stories.

I look at earnings announcements and find that 15-20% of the anomalies from the first chapter is concentrated in the three days around the earnings announcement. This pattern can be partly explained by the shift in the betas at the announcement date, which is roughly consistent with my model. The only anomaly whose concentration at the announcement cannot be explained by the beta shift is the value effect.

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A Proofs

This Appendix collects the proofs of the propositions in text. Some prepositions refer to the simulations described in Appendix B.

Proposition 1. The value of the firm is given by

$$dV_t/V_t = (r + \pi_B - (\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}) \cdot \frac{P_t}{V_t})dt + \Phi(d_1) \frac{S_t}{V_t} (\sigma_S dW_S + \sigma_I dW_I) + \sigma_B \frac{B_t}{V_t} dW_B \quad (26)$$

where

$$d_1 = \frac{\log(S/K) + (r + \sigma_C^2/2 + \sigma_I^2/2)(T - t)}{\sqrt{(\sigma_C^2 + \sigma_I^2) \cdot (T - t)}} \quad (27)$$

The expected rate of return to the firm (the drift in the firm value, μ_V) decreases in idiosyncratic risk, σ_I , and increases in the value of assets in place, B .

Proof: Black and Scholes (1973) formula in my case yields

$$P_t = S_t \Phi(d_1) - \exp(r(T - t)) K \Phi(d_2) \quad (28)$$

where $\Phi(\cdot)$ is the normal cdf, d_1 is as defined in (26), and $d_2 = d_1 - \tilde{\sigma}$.

Applying the Ito's lemma and the no-arbitrage condition to the value of the firm, $V_t = P_t + B_t$, I find that the value of the firm follows

$$dV_t/V_t = (r + \pi_S \cdot \Phi(d_1) \frac{S_t}{V_t} + \pi_B \frac{B_t}{V_t})dt + \Phi(d_1) \frac{S_t}{V_t} (\sigma_S dW_S + \sigma_I dW_I) + \sigma_B \frac{B_t}{V_t} dW_B \quad (29)$$

Then I rearrange the expression for the drift

$$\mu_V = r + \pi_S \Phi(d_1) \frac{S_t}{V_t} + \pi_B \frac{B_t}{V_t} = r + \pi_B - [\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}] \cdot \frac{P_t}{V_t} \quad (30)$$

Determining the sign of the drift's derivatives with respect to idiosyncratic risk and assets in place is now simple and intuitive. The term in the square brackets is positive if assets in place earn higher returns than growth options, which is a sufficient condition to derive the value effect. The changes in assets in place, B_t , influence only the denominator of the last term in (29). As B_t increases, V_t increases as well, and the whole last term decreases if $(\pi_B - \pi_S \Phi(d_1) S_t/P_t) > 0$, meaning that an increase in B_t causes an increase in expected returns. Algebraically,

$$\frac{\partial \mu_V}{\partial B} = \frac{P_t}{V_t^2} \cdot (\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}) > 0, \quad (31)$$

An increase in idiosyncratic risk, σ_I , increases the price of growth options, P_t , and their fraction in the value of the firm, P_t/V_t . An increase in idiosyncratic risk also leads to a decrease in the option elasticity with respect to the price of the underlying asset, $\Phi(d_1)S_t/P_t$, (see Galai and Masulis, 1976, for a proof). Therefore, both parts of the last term in (29) increase as idiosyncratic risk increases, and expected returns decrease. Algebraically,

$$\frac{\partial \mu_V}{\partial \omega} = \pi_S \frac{\partial(\Phi(d_1)S_t/P_t)}{\partial \omega} \cdot \frac{P_t}{V_t} - (\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}) \cdot \frac{B_t}{V_t^2} \cdot \frac{\partial P_t}{\partial \omega} < 0, \quad (32)$$

where the first term captures the effect of idiosyncratic risk on the option elasticity, and the second term captures the increase in the relative weight of growth options.

QED

Corollary 1. Define $IVar$ as the variance of the part of the return generating process (6), which is orthogonal to the pricing kernel. Then the idiosyncratic variance $IVar$ is

$$\begin{aligned} IVar = & \sigma_S^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} \cdot (1 - \rho_{S\Lambda}^2) + \sigma_B^2 \cdot \frac{B^2}{V^2} \cdot (1 - \rho_{B\Lambda}^2) + \\ & + \sigma_I^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} + \sigma_S \cdot \sigma_B \cdot \Phi(d_1) \cdot \frac{S}{V} \cdot \frac{B}{V} \cdot (\rho_{SB} - \rho_{B\Lambda} \cdot \rho_{S\Lambda}) \end{aligned} \quad (33)$$

I show that for all reasonable parameter values σ_I

$$\frac{\partial IVar}{\partial \sigma_I} > 0, \quad (34)$$

which implies that my empirical measure of idiosyncratic volatility - the standard deviation of Fama-French model residuals - is a noisy but valid proxy for σ_I .

Proof: The orthogonal to dW_Λ part of any diffusion is $dW_\bullet - \rho_{\bullet\Lambda} \cdot dW_\Lambda$. Therefore, (32) can be rewritten as

$$\begin{aligned} dV_t/V_t = & (r + \pi_B - (\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}) \cdot \frac{P_t}{V_t}) dt + \\ & + [\Phi(d_1) \frac{S_t}{V_t} \cdot (\sigma_S(dW_S - \rho_{S\Lambda} dW_\Lambda) + \sigma_I dW_I) + \sigma_B \frac{B_t}{V_t} \cdot \\ & \cdot (dW_B - \rho_{B\Lambda} dW_\Lambda)] + [\sigma_S \Phi(d_1) \frac{S_t}{V_t} \cdot \rho_{S\Lambda} + \sigma_B \frac{B_t}{V_t} \cdot \rho_{B\Lambda}] dW_\Lambda \end{aligned} \quad (35)$$

where the first square bracket contains the part orthogonal to dW_Λ and the second square bracket contains the part driven by dW_Λ . The standard deviation of the first square bracket is the model measure of idiosyncratic volatility, and its most natural empirical estimate is

the standard deviation of an asset-pricing model's residuals (in the empirical part I choose the Fama-French model).

Applying Fubini's theorem and collecting terms yields, as claimed in Corollary 1, that the idiosyncratic variance is

$$\begin{aligned} IVar = & \sigma_S^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} \cdot (1 - \rho_{S\Lambda}^2) + \sigma_B^2 \cdot \frac{B^2}{V^2} \cdot (1 - \rho_{B\Lambda}^2) + \\ & + \sigma_I^2 \cdot \Phi^2(d_1) \cdot \frac{S^2}{V^2} + \sigma_S \cdot \sigma_B \cdot \Phi(d_1) \cdot \frac{S}{V} \cdot \frac{B}{V} \cdot (\rho_{SB} - \rho_{B\Lambda} \cdot \rho_{S\Lambda}) \end{aligned} \quad (36)$$

The analytical expression for the derivative of $IVar$ wrt σ_I is complicated, and its sign cannot be determined without simulations. The simulations (see the Appendix B) show that at all empirically plausible parameter values the idiosyncratic volatility increases with the idiosyncratic risk parameter σ_I . The idiosyncratic volatility is also impacted by other parameters, so it is a noisy, but valid proxy for σ_I .

QED.

Proposition 2. The effect of idiosyncratic risk on returns, $\left| \frac{\partial \mu_V}{\partial \sigma_I} \right|$, is increasing in the value of assets in place B .

Proof:

$$\frac{\partial^2 \mu_V}{\partial \sigma_I \partial B} = -\pi_S \frac{\partial(\Phi(d_1)S_t/P_t)}{\partial \sigma_I} \cdot \frac{P_t}{V_t^2} + (\pi_B - \pi_S \Phi(d_1) \frac{S_t}{P_t}) \cdot \frac{B - P}{V^3} > 0 \quad (37)$$

The first term is always positive, and the second term is positive if $B > P$ and negative otherwise. However, for small B the first term becomes relatively large. Simulations in Appendix B show that the derivative is positive except for the parameter value that imply total volatility of 70% per annum or more and market-to-book higher than 5. The simulations also show that for these extreme parameter values the expected return is about the same as for the parameter values yielding the positive derivative.

QED

Proposition 3 The elasticity of the risk premium in my model decreases (increases in the absolute magnitude) as idiosyncratic volatility increases:

$$\frac{\partial}{\partial \sigma_I} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) < 0 \quad (38)$$

The elasticity of the risk premium in my model increases (decreases in the absolute magnitude) as the value of assets in place increases:

$$\frac{\partial}{\partial B} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) > 0 \quad (39)$$

The second cross-derivative of the elasticity with respect to idiosyncratic volatility and assets in place is positive:

$$\frac{\partial^2}{\partial \sigma_I \partial B} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) > 0 \quad (40)$$

Proof: It turns out that the derivative in (38) is the easiest to sign:

$$\frac{\partial}{\partial B} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) = \frac{1}{\lambda_V^2} \cdot \left(\frac{\partial^2 \lambda_V}{\partial \sigma_I \partial B} \cdot \sigma_I \cdot \lambda_V - \frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\partial \lambda_V}{\partial B} \cdot \sigma_I \right) > 0 \quad (41)$$

The derivative in the first term of (40) is positive at reasonable parameter values (see Proposition 2) and the derivatives in the second term of (40) are positive and negative, respectively (see Proposition 1). So, at reasonable parameter values (40) is a sum of two positive terms.

$$\begin{aligned} \frac{\partial}{\partial \sigma_I} \left(\frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) &= \frac{1}{\lambda_V^2} \cdot \left(\left(\frac{\partial^2 \lambda_V}{\partial \sigma_I^2} \cdot \sigma_I + \frac{\partial \lambda_V}{\partial \sigma_I} \right) \cdot \lambda_V - \left(\frac{\partial \lambda_V}{\partial \sigma_I} \right)^2 \cdot \sigma_I \right) = \\ &= \frac{1}{\lambda_V} \cdot \left(\frac{\partial^2 \lambda_V}{\partial \sigma_I^2} \cdot \sigma_I + \frac{\partial \lambda_V}{\partial \sigma_I} \left(1 - \frac{\partial \lambda_V}{\partial \sigma_I} \cdot \frac{\sigma_I}{\lambda_V} \right) \right) \end{aligned} \quad (42)$$

The first term in (41) has an ambiguous sign and the second term is always negative. Simulations in Appendix B show that the first term is positive but small for empirically plausible parameters, and the overall sign of (41) is negative.

Taking the cross-derivative (39) is tedious and, as in the previous case, there is no obvious way to sign it without simulations. The simulations in Appendix B show that at reasonable parameter values it is positive.

QED

Proposition 4 The elasticity of the firm value with respect to idiosyncratic volatility increases with idiosyncratic volatility:

$$\frac{\partial}{\partial \sigma_I} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) > 0 \quad (43)$$

The elasticity of the firm value decreases in the value of assets in place:

$$\frac{\partial}{\partial B} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) < 0 \quad (44)$$

The second cross-derivative of the elasticity with respect to idiosyncratic volatility and assets in place is negative:

$$\frac{\partial^2}{\partial \sigma_I \partial B} \left(\frac{\partial V}{\partial \sigma_I} \cdot \frac{\sigma_I}{V} \right) < 0 \quad (45)$$

Proof: It turns out that the derivative in (43) is the easiest to sign. The value of growth options increases in idiosyncratic volatility, and the effect of idiosyncratic volatility is weaker if assets in place take a larger share of the firm value. Algebraically, the elasticity is the firm value derivative with respect to idiosyncratic volatility scaled by the firm value. The derivative is always positive and does not depend on the value of assets in place¹¹. The firm value increases in the value of assets in place, which makes the whole ratio (i.e., the elasticity) decrease in assets in place.

The derivatives in (42) and (44) are complicated. The simulations in Appendix B show that their values are always positive except for the extreme growth firms (in the model, the market-to-book higher than 5 and annual total volatility higher than 50% per annum). However, the elasticity for those firms is still much larger than the elasticity of most other firms.

¹¹The fact that the call option value increases in volatility is widely known in finance. The respective derivative is called vega and equals to $P \cdot \exp(-r \cdot (T - t)) \phi(d_1) \sqrt{T - t}$.

B Simulations

This appendix collects the simulations the proofs in the Appendix of the paper refer to. The simulations show that even in the absence of the idiosyncratic volatility hedging channel idiosyncratic volatility has material impact on expected returns and the value effect magnitude (about 5% per year). The simulations also show that for high volatility growth firms expected returns are the lowest, and the risk premium elasticity and the firm value elasticity with respect to idiosyncratic volatility are the largest in absolute magnitude. The elasticities imply that the expected returns of high volatility growth firms can decrease by about a quarter and the value of these firms can increase by 15-20% as the idiosyncratic volatility increases in recessions.

B.1 Parameter Values

In the simulations, I fix two sets of parameter values. The first set is the moments of the three processes: the pricing kernel, Λ_t , the value of the assets in place, B_t , and the value of the asset behind the growth options, S_t . The values of the parameters are chosen so that the value effect roughly matches its empirical magnitude (about 6% per year). In the current setup, to keep things simple, I assume that the difference in expected returns between B_t and S_t is large enough to produce the positive value effect. It turns out that because the growth options are a highly levered claim on S_t , I have to assume quite large difference in the expected returns to S_t and B_t . The way to avoid it is to formally model the idiosyncratic volatility hedging channel, which I leave for future research. In my world, the idiosyncratic volatility hedging channel is responsible for explaining why the value effect can ever be positive, but the model is potentially open for incorporating other explanations.

I fix the volatility of the pricing kernel, σ_Λ , at 50% per year, the volatility of the asset behind the growth options, σ_S , at 10% per year, and the correlation between the asset behind the growth options and the pricing kernel, $\rho_{S\Lambda}$, at -0.8, which yields the risk premium $\pi_S = -\rho_{S\Lambda}\sigma_\Lambda\sigma_S = 4\%$. I also fix the volatility of the assets in place, σ_B , at 40% per year, and their correlation with the pricing kernel, $\rho_{B\Lambda}$, at -0.7, which yields the risk premium $\pi_B = -\rho_{B\Lambda}\sigma_\Lambda\sigma_B = 14\%$. All simulations produce similar results for other combinations of the parameters values that yield the risk premiums of 4% and 14%. In the

simulations of the idiosyncratic variance from Corollary 1, equation (8) or (36), I assume that the correlation between S_t and B_t is 0.5, but setting it to another value does not affect the results.

The second set of parameters describes the growth options. I assume that the current value of the asset behind them is 100 and the strike price is 90. My model is scale-invariant, so these values only mean that the asset is slightly in the money. The expiration period is set at 4 years. In what follows, I will discuss how the change in the maturity and the moneyness of the growth options affect my results. The overall conclusion is that my results are robust to reasonable variations in the maturity and the moneyness.

The two other parameters that vary freely in my tests are σ_I , the volatility of the purely idiosyncratic part in S_t , and B , the value of the assets in place. Varying these two parameters gives me a rich cross-section in terms of idiosyncratic volatility, $\sqrt{IVar}$, and market-to-book, V/B . As σ_I varies from 0% to 70% per annum, and B varies from 0 to 150, the idiosyncratic volatility varies between 20% and 80% per annum, and the market-to-book varies from 1.5 to above 6¹².

B.2 The Magnitude of the Three Idiosyncratic Volatility Effects

The top figure in Figure 1 shows the variation in the expected return as a function of the idiosyncratic volatility parameter, σ_I , and the value of the assets in place, B . First, I notice that idiosyncratic volatility is always negatively related to returns. Consistent with what my model predicts, the idiosyncratic volatility discount varies from 7% per year for growth firms ($B = 10$, $V/B \in [4, 7]$) to 2% per year for value firms ($B = 150$, $V/B \in [1.2, 1.4]$). The value effect varies with idiosyncratic volatility from 0.2% per year for low volatility firms ($\sigma_I = 5\%$ per year, $\sqrt{IVar} \in [20\%, 25\%]$) to 5.5% per year for high volatility firms ($\sigma_I = 70\%$ per year, $\sqrt{IVar} \in [50\%, 100\%]$).

Overall, my model produces numerically large effects of idiosyncratic volatility on expected returns. These effects are smaller than their empirical counterparts, because the simulations do not account for the aggregate volatility risk. I also fix the baseline parame-

¹²The lowest possible value of market-to-book in my model is 1. The market value, or the firm value V_t , differs from the book value, or the value of the assets in place B_t , by the always positive value of the growth options, P_t .

ters quite conservatively. For example, for some firms in the data the risk premium spread between the assets in place and the asset behind the growth options can be larger, which would magnify the idiosyncratic volatility effects.

In the bottom two graphs I look at the effect of varying the parameters of the growth options on the three idiosyncratic volatility effects. In the bottom left graph I reproduce the top graph with a higher strike price, $K = 100$, which makes the growth options exactly at the money. As expected, the idiosyncratic volatility effects become stronger, because at-the-money options are the most sensitive to volatility. The idiosyncratic volatility discount now varies from 9% per year for growth firms to 2% per year for value firms. I also see the negative value effect of -2% per year for low volatility firms. The value effect becomes positive as idiosyncratic volatility goes up and reaches 6% per year for high volatility firms.

Naturally, if I push the growth options deeper in the money, the effect is the reverse of what is in the bottom left graph in Figure 1, i.e., the value effect for low volatility firms increases, and the three idiosyncratic volatility effects decline. However, even if the value of the asset behind the growth options exceeds the strike price by a factor of 1.5, the idiosyncratic volatility effects are at least 3% per year.

In the bottom right graph, I reproduce the top graph with a shorter maturity of the growth options equal to 2 years. It makes the idiosyncratic volatility effects stronger. The reason is the slight convexity of expected return in idiosyncratic volatility that can be seen in the top graph in Figure 1. If the total life-time volatility of the option is smaller, the effect of the changes in it is stronger. With the maturity of the growth options equal to 2 years the idiosyncratic volatility discount varies from 10% per year for growth firms to 2.5% per year for value firms. The value effect changes from -3.5% per year for low volatility firms to 5.5% per year for high volatility firms. If I increase the maturity to 8 years, the idiosyncratic volatility discount varies from 4% to 1.5%, and the value effect varies from 6.5% to 4.5%.

The slight convexity of the graphs in idiosyncratic volatility does not contradict the empirical finding that the idiosyncratic volatility discount is driven by the firms in the highest volatility quintile. Because idiosyncratic volatility in the data is extremely positively skewed, the highest volatility quintile spans a huge spread in the idiosyncratic volatility, about half of the values in the graph.

B.3 Simulations for Corollary 1

In Corollary 1 I claim that the idiosyncratic variance, $IVar$, monotonically increases with the idiosyncratic volatility parameter, σ_I . The idiosyncratic variance is defined as the variance of the part of the firm value that is orthogonal to the pricing kernel. The idiosyncratic volatility parameter measures the volatility of the purely idiosyncratic part of the process for the asset behind the growth options.

The top graph in Figure 2 shows that the idiosyncratic variance indeed increases with σ_I . The value of the assets in place is fixed at 50, which implies the market-to-book between 1.6 and 2.2. The increase is quite strong and becomes stronger, as σ_I increases and begins to take a larger fraction of the idiosyncratic variance.

In unreported results, I tried the values of the assets in place between 10 and 150, which spans the market-to-book values between 1.15 and 7, and the relation between $IVar$ and σ_I never turned negative.

B.4 Simulations for Proposition 2

In Proposition 2 I claim that the idiosyncratic volatility discount increases with market-to-book and the value effect increases with idiosyncratic volatility. Algebraically, it means that the second cross-derivative of the expected return with respect to idiosyncratic volatility and the value of the assets in place is positive. The more assets in place the firm has, the weaker is the negative relation between the expected return and the idiosyncratic volatility, because the idiosyncratic volatility effects work through the growth options.

In Figure 1, I show that this assertion is true for all reasonable parameter values and the highest volatility growth firms have the lowest expected returns. In the bottom of Figure 2, I look at the cross-derivative graph and, expectedly, find that the derivative is positive almost everywhere. The exception is the bottom right corner, where the derivative dips to zero. The corner is populated by the extremely high volatility firms (total volatility of more than 70% per year) with extremely high market-to-book (more than 6). For these values, which are, at least, quite uncommon empirically, the derivative can become negative and the relations claimed in Proposition 2 can reverse. However, the rest of the bottom graph in Figure 2 and the graphs in Figure 1 show that the claimed relations embrace almost all empirically plausible parameter values.

B.5 Simulations for Proposition 3

Proposition 3 asserts that the elasticity of the risk premium with respect to idiosyncratic volatility decreases in idiosyncratic volatility and market-to-book. I use this fact to state that the increase in the expected risk premium in recessions, when idiosyncratic volatility is high, is the smallest for high volatility, growth, and high volatility growth firms. Proposition 3 implies that these firms have lower betas in recession and their value decreases the least when the economy slides into recession. In the paper, I use this fact to predict that these firms hedge against aggregate volatility risk.

In the simulations, I need to determine the sign of two derivatives of the elasticity - one with respect to idiosyncratic volatility, and one with respect to idiosyncratic volatility and the value of the assets in place. I start with looking at the graph of the elasticity in the top part of Figure 3.

The graph shows that the elasticity declines (increases in the absolute magnitude) in market-to-book and idiosyncratic volatility. The elasticity is the lowest for high volatility growth firms. The the elasticity is substantial and can reach -0.5. Given that the 50% increase in idiosyncratic volatility is not uncommon in recessions, the expected risk premium of high volatility growth firms can easily be cut by a quarter in bad times compared to what it could have been in the absence of idiosyncratic volatility.

I also see on the graph that the elasticity can increase (decrease in the absolute magnitude) in idiosyncratic volatility as both idiosyncratic volatility and market-to-book are high enough. In the bottom left graph, which shows the derivative of the elasticity with respect to idiosyncratic volatility, I see that the derivative is negative in the bottom right corner. The total volatility of the firms in the corner exceeds 50% per year, and their market-to-book exceeds 5, which is quite rare empirically. Even for these firms, as the top graph in Figure 3 shows, the elasticity remains much larger than the elasticity for the firms with more usual values of volatility and market-to-book (the center of the graph).

In the bottom right graph I plot the cross-derivative of the elasticity with respect to idiosyncratic volatility and market-to-book. Proposition 3 says that the derivative should be positive, which is the sufficient condition for the elasticity being the highest for high volatility growth firms. I see in the graph that the derivative turns negative for high volatility growth firms. The region of the wrong sign is broader than in the bottom left graph. The derivative can in fact be negative for total volatility of 45% per year and

market-to-book of 3.5, which is empirically plausible. However, the graph of the elasticity itself shows that high volatility growth firms do have large negative elasticity, which is much higher than the elasticity of most firms.

B.6 Simulations for Proposition 4

In Proposition 4 I look at the elasticity of the firm value with respect to idiosyncratic volatility. I claim that the elasticity is the most positive for high volatility, growth, and especially high volatility growth firms. Algebraically, it means that the derivative of the elasticity with respect to idiosyncratic volatility is positive, and the cross-derivative with respect to idiosyncratic volatility and the value of the assets in place should be negative¹³. Economically, it means that the value of high volatility, growth, and high volatility growth firms increases, as the idiosyncratic volatility increases and the economy slides into recession. In the paper, I use this fact as another way to explain why these firms hedge against aggregate volatility risk.

The top graph in Figure 4 plots the elasticity of the firm value with respect to idiosyncratic volatility. The elasticity is substantial and increases with idiosyncratic volatility and the value of assets in place. The elasticity values of 0.3 and higher are not unusual and start at the parameter values implying total volatility of 40% and market-to-book of 2.5. The elasticity of 0.3 implies that the volatility increase in recessions can increase the firm value by 15%, just because growth options are more valuable in a volatile environment.

In the bottom left graph I plot the derivative of the elasticity with respect to idiosyncratic volatility and find that it is always positive. In the bottom right part I plot the derivative of the elasticity with respect to idiosyncratic volatility and the value of the assets in place. The derivative does become negative in the bottom right corner, populated by the firms with extremely high volatility and market-to-book. The firms in the area have total volatility higher than 50% per year and market-to-book exceeding 4, which is quite rare empirically. However, the top graph shows that even the wrong sign of the second derivative does not really compromise the conclusion of Proposition 4 that the firm value of high volatility growth firms responds most positively to volatility increases.

¹³The fact that the derivative with respect to the value of the assets in place is negative was proven in the Appendix A

Table 1. Descriptive Statistics

The table presents descriptive statistics for the idiosyncratic volatility quintiles. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each month (at least 15 valid observations are required). The idiosyncratic volatility quintile portfolios are formed at the end of each calendar month based on the idiosyncratic volatility estimated in this month, and held for one month afterwards. Panel A shows the raw returns and the Fama-French alphas (both equal-weighted and value-weighted) to the idiosyncratic volatility quintile portfolios formed using CRSP quintile breakpoints. Panel B repeats the same for the portfolios formed using NYSE breakpoints. NYSE firms are defined as firms with `exchcd=1`, where `exchcd` is the listing indicator at the portfolio formation date from the CRSP events file. In Panel C I report the Fama-French factor betas the means of size and market-to-book for the portfolios from Panel B. Size is defined as shares outstanding times price from the CRSP monthly returns file. Market-to-book is defined as Compustat item #25 times Compustat item #199 divided by Compustat item #60 plus Compustat item #74. The returns and betas are measured in the month after the portfolio formation. Size and market-to-book are measured in the month of portfolio formation. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from July 1963 to December 2006.

Panel A. Returns, CRSP Breakpoints

	Low	IVol2	IVol3	IVol4	High	L-H
Raw EW	1.140	1.411	1.451	1.298	0.934	0.206
t-stat	<i>6.12</i>	<i>6.16</i>	<i>5.23</i>	<i>3.77</i>	<i>2.16</i>	<i>0.63</i>
FF EW	0.055	0.180	0.151	-0.057	-0.545	0.600
t-stat	<i>0.66</i>	<i>2.40</i>	<i>2.41</i>	<i>-0.78</i>	<i>-3.24</i>	<i>2.99</i>
Raw VW	0.970	1.072	1.096	0.787	0.003	0.967
t-stat	<i>5.79</i>	<i>5.43</i>	<i>4.28</i>	<i>2.42</i>	<i>0.01</i>	<i>3.01</i>
FF VW	0.055	0.071	0.031	-0.356	-1.269	1.324
t-stat	<i>1.12</i>	<i>1.38</i>	<i>0.44</i>	<i>-3.50</i>	<i>-7.87</i>	<i>6.86</i>

Panel B. Returns, NYSE Breakpoints

	Low	IVol2	IVol3	IVol4	High	L-H
Raw EW	1.085	1.371	1.450	1.477	1.131	-0.046
t-stat	<i>5.89</i>	<i>6.26</i>	<i>5.96</i>	<i>5.20</i>	<i>2.96</i>	<i>-0.17</i>
FF EW	0.486	0.645	0.654	0.606	0.169	0.317
t-stat	<i>5.59</i>	<i>7.83</i>	<i>8.08</i>	<i>8.21</i>	<i>1.56</i>	<i>2.22</i>
Raw VW	0.980	1.087	1.067	1.154	0.688	0.292
t-stat	<i>5.90</i>	<i>5.73</i>	<i>4.91</i>	<i>4.48</i>	<i>2.06</i>	<i>1.16</i>
FF VW	0.077	0.099	0.014	0.049	-0.517	0.594
t-stat	<i>1.60</i>	<i>1.96</i>	<i>0.22</i>	<i>0.65</i>	<i>-4.92</i>	<i>4.34</i>

Panel C. Fama-French Betas, Size, and Market-to-Book, NYSE Breakpoints

	Low	IVol2	IVol3	IVol4	High	L-H
β_{MKT}	0.874	1.025	1.118	1.196	1.266	-0.392
t-stat	<i>60.1</i>	<i>55.0</i>	<i>48.8</i>	<i>42.5</i>	<i>35.7</i>	<i>-8.57</i>
β_{SMB}	-0.256	-0.148	0.021	0.268	0.815	-1.071
t-stat	<i>-11.4</i>	<i>-6.34</i>	<i>0.40</i>	<i>4.2</i>	<i>15.4</i>	<i>-18.1</i>
β_{HML}	0.172	0.141	0.092	-0.009	-0.163	0.336
t-stat	<i>3.62</i>	<i>2.61</i>	<i>1.93</i>	<i>-0.14</i>	<i>-2.40</i>	<i>3.21</i>
Size	2511	1956	1175	598	176	2335
t-stat	<i>7.80</i>	<i>8.86</i>	<i>8.37</i>	<i>7.88</i>	<i>7.25</i>	<i>7.71</i>
M/B	2.733	2.514	2.547	2.700	3.789	-1.055
t-stat	<i>13.2</i>	<i>20.5</i>	<i>23.6</i>	<i>25.9</i>	<i>21.0</i>	<i>-4.97</i>

Table 2. Double Sorts: Fama-French Abnormal Returns

The table presents monthly Fama-French abnormal returns to the 25 idiosyncratic volatility - market-to-book portfolios, sorted independently using NYSE (`exchcd=1`) breakpoints. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The idiosyncratic volatility (market-to-book) portfolios are rebalanced monthly (annually). Market-to-book is defined as Compustat item #25 times Compustat item #199 divided by Compustat item #60 plus Compustat item #74. Panel A shows value-weighted returns and Panel B reports equal-weighted returns. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006.

Panel A. Value-Weighted Returns							Panel B. Equal-Weighted Returns						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	-0.001	0.068	0.172	0.080	-0.104	0.103	Value	0.203	0.283	0.479	0.386	0.528	-0.325
t-stat	<i>-0.01</i>	<i>0.44</i>	<i>1.07</i>	<i>0.47</i>	<i>-0.63</i>	<i>0.48</i>	t-stat	<i>1.63</i>	<i>3.02</i>	<i>4.85</i>	<i>3.64</i>	<i>3.54</i>	<i>-1.81</i>
MB 2	0.028	0.032	-0.145	-0.020	-0.293	0.321	MB 2	0.008	0.249	0.139	0.261	-0.053	0.061
t-stat	<i>0.25</i>	<i>0.26</i>	<i>-1.22</i>	<i>-0.13</i>	<i>-2.02</i>	<i>1.66</i>	t-stat	<i>0.09</i>	<i>2.71</i>	<i>1.50</i>	<i>2.81</i>	<i>-0.49</i>	<i>0.42</i>
MB 3	0.028	0.019	-0.058	-0.091	-0.435	0.462	MB 3	-0.039	0.110	0.180	0.179	-0.120	0.081
t-stat	<i>0.25</i>	<i>0.16</i>	<i>-0.50</i>	<i>-0.66</i>	<i>-2.73</i>	<i>2.46</i>	t-stat	<i>-0.38</i>	<i>1.14</i>	<i>1.99</i>	<i>2.25</i>	<i>-0.91</i>	<i>0.47</i>
MB 4	0.179	0.070	0.018	-0.100	-0.309	0.488	MB 4	-0.064	0.098	0.117	0.115	-0.335	0.270
t-stat	<i>1.75</i>	<i>0.69</i>	<i>0.18</i>	<i>-0.85</i>	<i>-2.08</i>	<i>2.66</i>	t-stat	<i>-0.61</i>	<i>1.00</i>	<i>1.26</i>	<i>1.35</i>	<i>-3.02</i>	<i>1.59</i>
Growth	0.273	0.299	0.191	0.249	-0.565	0.838	Growth	-0.029	0.115	0.154	-0.010	-0.677	0.648
t-stat	<i>2.35</i>	<i>3.34</i>	<i>1.62</i>	<i>1.92</i>	<i>-3.89</i>	<i>3.92</i>	t-stat	<i>-0.24</i>	<i>0.90</i>	<i>1.48</i>	<i>-0.11</i>	<i>-5.01</i>	<i>3.34</i>
V-G	-0.275	-0.231	-0.019	-0.169	0.461	0.735	V-G	0.233	0.168	0.325	0.396	1.206	0.973
t(V-G)	<i>-1.50</i>	<i>-1.28</i>	<i>-0.10</i>	<i>-0.88</i>	<i>2.47</i>	<i>2.80</i>	t(V-G)	<i>1.86</i>	<i>1.39</i>	<i>2.72</i>	<i>3.02</i>	<i>8.23</i>	<i>4.92</i>

Table 3. Fama-MacBeth Regressions

Panel B presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. The independent variables are the current-month (Panel A) or the previous-month (Panel B) market beta, the percentage rank of previous year market capitalization, the percentage rank of previous year market-to-book, the percentage rank of previous month idiosyncratic volatility. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). Market-to-book is defined as Compustat item #25 times Compustat item #199 divided by Compustat item #60 plus Compustat item #74. The R-squared is the average R-squared across all months. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006.

	Panel A. Current Beta				Panel B. Lagged Beta			
	1	2	3	4	5	6	7	8
Beta	0.317	0.345	0.347	0.348	-0.042	-0.037	-0.030	-0.036
t-stat	6.08	7.04	6.97	7.10	-1.57	-1.75	-1.37	-1.70
Size	-0.0102	-0.0149	-0.0158	-0.0156	-0.0068	-0.0097	-0.0109	-0.0104
t-stat	-2.75	-4.95	-5.08	-5.20	-2.09	-3.53	-3.92	-3.76
M/B	-0.0109	-0.0092	0.0034	0.0050	-0.0108	-0.0094	-0.0001	0.0035
t-stat	-3.81	-3.71	1.29	1.90	-4.37	-4.98	-0.03	1.68
IVol		-0.0098		0.0016		-0.0061		0.0043
t-stat		-3.11		0.53		-1.67		1.43
IVol*M/B			-0.00022	-0.00024			-0.00016	-0.00022
t-stat			-4.35	-6.31			-2.68	-5.73
R-sq	0.034	0.043	0.042	0.045	0.025	0.035	0.034	0.036
Adj R-sq	0.032	0.041	0.040	0.042	0.024	0.033	0.032	0.034

Table 4. Is the BVIX Factor Priced?

Panel A reports the value-weighted returns to the aggregate volatility sensitivity quintiles. The quintiles are sorted from the most negative to the most positive sensitivity in the previous month. The return sensitivity to aggregate volatility is measured separately for each firm-month by running stock excess returns on market excess returns and the VIX index change using daily data (at least 15 non-missing returns are required). The VIX index is from CBOE. It measures the implied volatility of the one-month S&P100 options. The sensitivity portfolios are rebalanced monthly and held for one month. The last column reports the difference in returns between the lowest and the highest sensitivity quintiles (the BVIX factor).

Panel B reports the GRS statistics for different portfolios sets - the 25 idiosyncratic volatility - market-to-book portfolios from Table 2, the 25 size - market-to-book portfolios from Fama and French (1992), and the 48 industry portfolios from Fama and French (1997). For the CAPM and the Fama-French model the GRS statistics test if all alphas are jointly zero. For the ICAPM with the BVIX factor, I test if all alphas are jointly zero and if all BVIX betas are jointly zero. The returns to all portfolio sets are equal-weighted. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period is from February 1986 to December 2006.

Panel A. Value-Weighted Returns to Volatility Sensitivity Quintiles

	VIX 1	VIX 2	VIX 3	VIX 4	VIX 5	BVIX
Raw	1.342	1.077	1.074	1.008	0.462	0.880
t-stat	3.92	4.28	4.43	3.54	1.19	4.15
CAPM	0.216	0.097	0.102	-0.027	-0.765	0.981
t-stat	1.62	1.20	1.24	-0.37	-4.21	4.20
FF	0.271	0.049	0.048	-0.048	-0.584	0.856
t-stat	1.90	0.73	0.75	-0.64	-3.66	3.71

Panel B. BVIX Factor Pricing for Different Portfolio Sets

25 IVol - M/B portfolios				
	α_{CAPM}	α_{FF}	α_{ICAPM}	β_{BVIX}
GRS	4.129	3.427	3.978	3.721
p-value	0.000	0.000	0.000	0.000
25 Size - M/B portfolios				
	α_{CAPM}	α_{FF}	α_{ICAPM}	β_{BVIX}
GRS	4.129	3.721	3.427	3.978
p-value	0.000	0.000	0.000	0.000
48 industry portfolios				
	α_{CAPM}	α_{FF}	α_{ICAPM}	β_{BVIX}
GRS	1.787	1.849	1.676	1.997
p-value	0.003	0.002	0.008	0.001

Table 5. Aggregate Volatility Risk Loadings

The table presents the BVIX betas of the 25 idiosyncratic volatility - market-to-book portfolios. The portfolios are sorted independently using NYSE (`exchcd=1`) breakpoints. The BVIX betas are estimated from the ICAPM with the BVIX factor. The BVIX factor is the difference in value-weighted returns between the quintiles of firms with the lowest and highest sensitivity of returns to the changes in the VIX index. The return sensitivity to changes in the VIX index is measured separately for each firm-month by running stock excess returns on market excess returns and the VIX change using daily data (at least 15 non-missing returns are required). The return sensitivity portfolios are formed at the end of each month based on this month return sensitivities and held for one month. The idiosyncratic volatility (market-to-book) portfolios are rebalanced monthly (annually). Panel A shows the results for value-weighted returns, and Panel B reports the results for equal-weighted returns. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Value-Weighted Returns							Panel B. Equal-Weighted Returns						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	0.186	0.127	0.066	0.230	-0.013	0.199	Value	0.061	0.051	0.022	0.012	-0.115	0.176
t-stat	<i>2.05</i>	<i>0.92</i>	<i>0.53</i>	<i>2.44</i>	<i>-0.14</i>	<i>1.99</i>	t-stat	<i>1.21</i>	<i>0.83</i>	<i>0.34</i>	<i>0.20</i>	<i>-0.68</i>	<i>1.11</i>
MB 2	0.059	0.089	0.104	0.061	-0.186	0.245	MB 2	0.031	0.066	0.038	0.002	-0.196	0.227
t-stat	<i>0.67</i>	<i>0.81</i>	<i>0.84</i>	<i>0.60</i>	<i>-1.42</i>	<i>1.19</i>	t-stat	<i>0.51</i>	<i>1.07</i>	<i>0.52</i>	<i>0.03</i>	<i>-1.38</i>	<i>1.37</i>
MB 3	0.057	0.186	0.125	0.037	-0.114	0.172	MB 3	0.082	0.074	0.050	-0.023	-0.257	0.340
t-stat	<i>0.72</i>	<i>1.72</i>	<i>1.50</i>	<i>0.60</i>	<i>-1.59</i>	<i>1.54</i>	t-stat	<i>1.28</i>	<i>1.09</i>	<i>0.72</i>	<i>-0.38</i>	<i>-1.56</i>	<i>1.73</i>
MB 4	0.172	0.295	0.194	-0.017	-0.201	0.374	MB 4	0.041	0.101	0.036	-0.068	-0.348	0.390
t-stat	<i>2.40</i>	<i>3.98</i>	<i>2.31</i>	<i>-0.25</i>	<i>-3.21</i>	<i>3.39</i>	t-stat	<i>0.68</i>	<i>1.71</i>	<i>0.61</i>	<i>-1.26</i>	<i>-2.26</i>	<i>2.28</i>
Growth	0.209	0.024	0.062	-0.030	-0.395	0.604	Growth	0.175	0.113	0.004	-0.160	-0.527	0.702
t-stat	<i>3.91</i>	<i>0.51</i>	<i>0.83</i>	<i>-0.44</i>	<i>-2.94</i>	<i>3.57</i>	t-stat	<i>2.47</i>	<i>2.24</i>	<i>0.11</i>	<i>-2.20</i>	<i>-2.56</i>	<i>2.67</i>
V-G	-0.023	0.104	0.004	0.260	0.382	0.405	V-G	-0.114	-0.063	0.017	0.172	0.412	0.526
t(V-G)	<i>-0.26</i>	<i>0.74</i>	<i>0.03</i>	<i>2.32</i>	<i>2.75</i>	<i>3.37</i>	t(V-G)	<i>-1.59</i>	<i>-1.39</i>	<i>0.36</i>	<i>2.17</i>	<i>4.01</i>	<i>3.57</i>

Table 6. Conditional CAPM Betas across Business Cycle

The table reports conditional CAPM betas across different states of the world for five arbitrage portfolios. IVol is the portfolio long in the low volatility quintile and short in the high volatility quintile. IVolh is long in low volatility growth portfolio and short in high volatility growth portfolio. HMLl (HMLh) is long in low (high) volatility value and short in low (high) volatility growth. IVol55 is long in high volatility growth portfolio and short in one-month Treasury bill. Recession (Expansion) is defined as the period when the expected market risk premium is higher (lower) than its in-sample mean. The expected risk premiums and the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. The left part of the table presents the results with value-weighted returns, and the right part looks at equal-weighted returns. The standard errors reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006.

	Value-Weighted			Equal-Weighted		
	Rec	Exp	Diff	Rec	Exp	Diff
IVol	-0.563	-0.765	0.202	-0.641	-0.734	0.093
se	<i>0.034</i>	<i>0.037</i>	<i>0.051</i>	<i>0.033</i>	<i>0.032</i>	<i>0.047</i>
IVolh	-0.521	-0.809	0.288	-0.533	-0.811	0.278
se	<i>0.038</i>	<i>0.044</i>	<i>0.061</i>	<i>0.046</i>	<i>0.051</i>	<i>0.071</i>
HMLl	-0.005	-0.075	0.070	-0.270	-0.198	-0.072
se	<i>0.008</i>	<i>0.009</i>	<i>0.012</i>	<i>0.013</i>	<i>0.013</i>	<i>0.018</i>
HMLh	-0.123	-0.409	0.286	-0.223	-0.447	0.223
se	<i>0.019</i>	<i>0.028</i>	<i>0.035</i>	<i>0.020</i>	<i>0.028</i>	<i>0.036</i>
IVol55	1.467	1.644	-0.177	1.468	1.616	-0.147
se	<i>0.022</i>	<i>0.025</i>	<i>0.035</i>	<i>0.035</i>	<i>0.034</i>	<i>0.048</i>

Table 7. Explaining the Idiosyncratic Volatility Effects

The table reports monthly alphas of the four arbitrage portfolios (IVol, IVolh, HMLh, and IVol55) described in the heading of Table 6. The asset-pricing models I fit to their returns are the CAPM, the Fama-French model (FF), and the ICAPM with BVIX. The BVIX factor is defined in the heading of Table 4. In the conditional versions of the models the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. Panel A and B report results for value- and equal-weighted returns, respectively. The standard errors reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from February 1986 to December 2006.

Panel A. Value-Weighted Returns

	Unconditional				Conditional		
	CAPM	FF	ICAPM		CAPM	ICAPM	
	α_{CAPM}	α_{FF}	α_{ICAPM}	β_{BVIX}	α_{CAPM}	α_{ICAPM}	β_{BVIX}
IVol	0.944	0.547	0.421	0.533	0.658	0.286	0.431
t-stat	<i>2.95</i>	<i>2.52</i>	<i>1.25</i>	<i>3.26</i>	<i>2.27</i>	<i>0.89</i>	<i>2.32</i>
IVolh	1.137	0.674	0.544	0.604	0.809	0.389	0.487
t-stat	<i>3.03</i>	<i>2.08</i>	<i>1.38</i>	<i>3.57</i>	<i>2.24</i>	<i>1.00</i>	<i>2.48</i>
HMLh	1.329	0.591	0.954	0.382	1.156	0.872	0.330
t-stat	<i>3.55</i>	<i>2.24</i>	<i>2.58</i>	<i>2.75</i>	<i>3.23</i>	<i>2.49</i>	<i>2.21</i>
IVol55	-0.831	-0.330	-0.443	-0.395	-0.645	-0.362	-0.328
t-stat	<i>-2.97</i>	<i>-1.55</i>	<i>-1.43</i>	<i>-2.94</i>	<i>-2.36</i>	<i>-1.20</i>	<i>-2.15</i>

Panel B. Equal-Weighted Returns

	Unconditional				Conditional		
	CAPM	FF	ICAPM		CAPM	ICAPM	
	α_{CAPM}	α_{FF}	α_{ICAPM}	β_{BVIX}	α_{CAPM}	α_{ICAPM}	β_{BVIX}
IVol	0.486	0.129	0.115	0.378	0.266	0.014	0.292
t-stat	<i>1.44</i>	<i>0.57</i>	<i>0.30</i>	<i>2.05</i>	<i>0.83</i>	<i>0.04</i>	<i>1.38</i>
IVolh	0.958	0.391	0.269	0.702	0.607	0.119	0.567
t-stat	<i>2.16</i>	<i>1.40</i>	<i>0.53</i>	<i>2.67</i>	<i>1.46</i>	<i>0.24</i>	<i>1.91</i>
HMLh	2.135	1.612	1.730	0.412	1.939	1.630	0.358
t-stat	<i>6.90</i>	<i>6.90</i>	<i>5.95</i>	<i>4.01</i>	<i>6.26</i>	<i>5.48</i>	<i>3.20</i>
IVol55	-0.951	-0.595	-0.434	-0.527	-0.749	-0.362	-0.449
t-stat	<i>-2.46</i>	<i>-2.82</i>	<i>-0.96</i>	<i>-2.56</i>	<i>-1.89</i>	<i>-0.78</i>	<i>-1.94</i>

Table 8. Aggregate Volatility Risk and the Small Growth Anomaly

The table shows equal-weighted (left panel) and value-weighted (right panel) alphas of the CAPM, the Fama-French model and the CAPM augmented with the BVIX factor (CAPMB), as well as the BVIX betas, for the size quintile portfolios in the lowest book-to-market quintile. The BVIX factor is the zero-investment portfolio long in the quintile of firms with the most negative return sensitivity to changes in the VIX index, and short in the quintile with the most positive sensitivity. The return sensitivity to changes in VIX index is measured separately for each firm-month by running stock excess returns on market excess returns and the VIX change using daily data (at least 15 non-missing returns are required). The VIX sensitivity quintiles are rebalanced monthly and held for one month. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity. The sample period is from February 1986 to December 2006.

Equal-Weighted Returns							Value-Weighted Returns						
Panel A. February 1986 - December 2006, January 2001 excluded													
	Small	Size2	Size3	Size4	Big	S-B		Small	Size2	Size3	Size4	Big	S-B
α_{CAPM}	-0.864	-0.754	-0.502	-0.141	-0.071	-0.794	α_{CAPM}	-1.009	-0.559	-0.397	-0.068	0.007	-1.016
t-stat	<i>-2.03</i>	<i>-3.19</i>	<i>-2.19</i>	<i>-0.73</i>	<i>-0.61</i>	<i>-1.81</i>	t-stat	<i>-2.93</i>	<i>-2.52</i>	<i>-1.98</i>	<i>-0.37</i>	<i>0.05</i>	<i>-2.64</i>
α_{FF}	-0.668	-0.507	-0.176	0.123	0.123	-0.791	α_{FF}	-0.707	-0.288	-0.028	0.236	0.237	-0.945
t-stat	<i>-2.58</i>	<i>-3.65</i>	<i>-1.35</i>	<i>0.95</i>	<i>1.69</i>	<i>-2.78</i>	t-stat	<i>-3.90</i>	<i>-2.67</i>	<i>-0.31</i>	<i>1.83</i>	<i>2.98</i>	<i>-4.63</i>
α_{ICAPM}	-0.429	-0.422	-0.238	0.026	-0.074	-0.355	α_{ICAPM}	-0.475	-0.175	-0.059	0.200	-0.065	-0.410
t-stat	<i>-0.91</i>	<i>-1.61</i>	<i>-1.05</i>	<i>0.13</i>	<i>-0.62</i>	<i>-0.71</i>	t-stat	<i>-1.03</i>	<i>-0.59</i>	<i>-0.24</i>	<i>0.85</i>	<i>-0.50</i>	<i>-0.83</i>
β_{BVIX}	-0.461	-0.352	-0.280	-0.176	0.004	-0.465	β_{BVIX}	-0.566	-0.407	-0.358	-0.284	0.075	-0.642
t-stat	<i>-2.96</i>	<i>-3.76</i>	<i>-5.67</i>	<i>-4.02</i>	<i>0.08</i>	<i>-2.36</i>	t-stat	<i>-2.48</i>	<i>-2.54</i>	<i>-2.74</i>	<i>-2.76</i>	<i>2.65</i>	<i>-2.63</i>

Equal-Weighted Returns

Value-Weighted Returns

Panel B. February 1986 - December 2006, January 2001 included

	Small	Size2	Size3	Size4	Big	S-B		Small	Size2	Size3	Size4	Big	S-B
α_{CAPM}	-0.679	-0.640	-0.396	-0.090	-0.045	-0.634	α_{CAPM}	-0.926	-0.525	-0.369	-0.058	0.004	-0.930
t-stat	<i>-1.62</i>	<i>-2.73</i>	<i>-1.90</i>	<i>-0.49</i>	<i>-0.42</i>	<i>-1.42</i>	t-stat	<i>-2.74</i>	<i>-2.35</i>	<i>-1.89</i>	<i>-0.32</i>	<i>0.03</i>	<i>-2.42</i>
α_{FF}	-0.462	-0.389	-0.064	0.172	0.155	-0.617	α_{FF}	-0.645	-0.280	-0.025	0.225	0.233	-0.879
t-stat	<i>-1.58</i>	<i>-2.24</i>	<i>-0.41</i>	<i>1.27</i>	<i>1.97</i>	<i>-2.05</i>	t-stat	<i>-3.55</i>	<i>-2.57</i>	<i>-0.28</i>	<i>1.77</i>	<i>2.96</i>	<i>-4.37</i>
α_{ICAPM}	-0.362	-0.380	-0.199	0.045	-0.066	-0.296	α_{ICAPM}	-0.440	-0.158	-0.046	0.207	-0.066	-0.374
t-stat	<i>-0.76</i>	<i>-1.44</i>	<i>-0.92</i>	<i>0.23</i>	<i>-0.56</i>	<i>-0.58</i>	t-stat	<i>-0.95</i>	<i>-0.53</i>	<i>-0.18</i>	<i>0.86</i>	<i>-0.51</i>	<i>-0.74</i>
β_{BVIX}	-0.323	-0.265	-0.201	-0.138	0.021	-0.344	β_{BVIX}	-0.495	-0.374	-0.330	-0.270	0.072	-0.567
t-stat	<i>-1.41</i>	<i>-1.84</i>	<i>-1.95</i>	<i>-2.31</i>	<i>0.43</i>	<i>-1.38</i>	t-stat	<i>-1.96</i>	<i>-2.22</i>	<i>-2.40</i>	<i>-2.58</i>	<i>2.54</i>	<i>-2.11</i>

Table 9. Aggregate Volatility Risk and the New Issues Puzzle

The table reports the results fitting the CAPM, the ICAPM with BVIX, and the Fama-French model to the IPO and SEO portfolios. The last row reports the percentage improvement of the ICAPM alpha over the CAPM alpha or the Fama-French alpha. The right part of each panel shows the results for the whole sample (February 1986 to December 2006), and the left part removes January 2001. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

Panel A. Equal-Weighted IPO Returns

	January 2001 excluded			January 2001 included		
	CAPM	ICAPM	FF	CAPM	ICAPM	FF
α	-0.702	-0.372	-0.536	-0.578	-0.326	-0.406
t-stat	<i>-2.27</i>	<i>-1.19</i>	<i>-2.97</i>	<i>-2.01</i>	<i>-1.08</i>	<i>-2.11</i>
β_{MKT}	1.446	1.387	1.237	1.466	1.423	1.228
t-stat	<i>18.2</i>	<i>20.3</i>	<i>17.7</i>	<i>16.4</i>	<i>15.7</i>	<i>16.7</i>
β_{SMB}			1.004			1.048
t-stat			<i>7.84</i>			<i>7.46</i>
β_{HML}			-0.161			-0.211
t-stat			<i>-1.25</i>			<i>-1.30</i>
β_{BVIX}		-0.376			-0.281	
t-stat		<i>-4.38</i>			<i>-1.99</i>	
$\Delta\alpha/\alpha$	47%		31%	44%		20%

Panel B. Equal-Weighted SEO Returns

	January 2001 excluded			January 2001 included		
	CAPM	ICAPM	FF	CAPM	ICAPM	FF
α	-0.506	-0.271	-0.486	-0.436	-0.245	-0.415
t-stat	<i>-2.67</i>	<i>-1.37</i>	<i>-4.20</i>	<i>-2.25</i>	<i>-1.22</i>	<i>-3.16</i>
β_{MKT}	1.306	1.265	1.208	1.318	1.286	1.203
t-stat	<i>24.7</i>	<i>27.5</i>	<i>22.3</i>	<i>23.2</i>	<i>23.2</i>	<i>21.6</i>
β_{SMB}			0.751			0.775
t-stat			<i>7.96</i>			<i>7.54</i>
β_{HML}			0.046			0.019
t-stat			<i>0.59</i>			<i>0.20</i>
β_{BVIX}		-0.257			-0.203	
t-stat		<i>-6.09</i>			<i>-2.65</i>	
$\Delta\alpha/\alpha$	46%		44%	44%		41%

Table 10. The BVIX factor versus the Investment Factor

The table reports the results of fitting to the new issues portfolios the ICAPM with the BVIX factor, the investment factor, or both. The last row reports the percentage improvement in the alpha after augmenting CAPM with the factor(s). The right part of each panel shows the results for the whole sample (February 1986 to December 2006), and the left part removes January 2001. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

Panel A. IPO: EW ICAPM Alphas							Panel B. SEO: EW ICAPM Alphas						
	w/o January 2001			with January 2001				w/o January 2001			with January 2001		
	BVIX	INV	Both	BVIX	INV	Both		BVIX	INV	Both	BVIX	INV	Both
α	-0.372	-0.326	-0.003	-0.326	-0.088	0.179		-0.271	-0.177	0.053	-0.245	-0.050	0.153
t-stat	<i>-1.19</i>	<i>-1.03</i>	<i>-0.01</i>	<i>-1.08</i>	<i>-0.25</i>	<i>0.58</i>		<i>-1.37</i>	<i>-0.96</i>	<i>0.27</i>	<i>-1.22</i>	<i>-0.22</i>	<i>0.71</i>
β_{MKT}	1.387	1.327	1.269	1.423	1.303	1.256		1.265	1.202	1.162	1.286	1.189	1.155
t-stat	<i>20.3</i>	<i>14.6</i>	<i>18.2</i>	<i>15.7</i>	<i>14.0</i>	<i>17.8</i>		<i>27.5</i>	<i>20.4</i>	<i>24.0</i>	<i>23.2</i>	<i>19.6</i>	<i>23.2</i>
β_{BVIX}	-0.376		-0.374	-0.281		-0.288		-0.257		-0.255	-0.203		-0.208
t-stat	<i>-4.38</i>		<i>-3.58</i>	<i>-1.99</i>		<i>-1.87</i>		<i>-6.09</i>		<i>-4.64</i>	<i>-2.65</i>		<i>-2.47</i>
β_{INV}		-0.589	-0.582		-0.790	-0.804			-0.515	-0.510		-0.623	-0.633
t-stat		<i>-2.37</i>	<i>-2.94</i>		<i>-2.33</i>	<i>-2.54</i>			<i>-3.61</i>	<i>-4.33</i>		<i>-3.51</i>	<i>-3.84</i>
$\Delta\alpha/\alpha$	47%	53%	100%	44%	85%	131%		46%	65%	110%	44%	89%	135%

Table 11. The New Issues Puzzle in Cross-Section

The table presents the results of estimating the CAPM augmented by the BVIX factor, the investment factor, both or none for the new issues portfolios in different size and market-to-book portfolios. The size and market-to-book portfolios are the top 30%, the middle 40%, and the bottom 30%. The market-to-book and size are measured in the month after the issue using the SDC data. Sorting on size is conditional on market-to-book. The alpha subscript in the rows shows the factor, with which I augment the CAPM. The sample period is from February 1986 to December 2001, January 2001 is excluded. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

Panel A. IPO: Equal-Weighted (I)CAPM Alphas

	MB1	MB2	MB3	3-1	Size1	Size2	Size3	1-3
α_{none}	0.211	-0.568	-0.970	1.181	-0.774	-0.612	0.258	1.031
t-stat	<i>0.78</i>	<i>-1.96</i>	<i>-2.48</i>	<i>3.68</i>	<i>-2.29</i>	<i>-1.83</i>	<i>0.92</i>	<i>2.40</i>
α_{BVIX}	0.327	-0.376	-0.533	0.860	-0.422	-0.298	0.335	0.757
t-stat	<i>1.26</i>	<i>-1.24</i>	<i>-1.36</i>	<i>2.61</i>	<i>-1.23</i>	<i>-0.92</i>	<i>1.15</i>	<i>1.71</i>
β_{BVIX}	-0.169	-0.212	-0.490	0.321	-0.393	-0.382	-0.111	0.281
t-stat	<i>-3.60</i>	<i>-2.62</i>	<i>-3.80</i>	<i>3.02</i>	<i>-4.04</i>	<i>-4.44</i>	<i>-2.00</i>	<i>2.54</i>
α_{INV}	0.514	-0.250	-0.605	1.119	-0.403	-0.165	0.460	0.863
t-stat	<i>1.77</i>	<i>-0.90</i>	<i>-1.46</i>	<i>3.63</i>	<i>-1.15</i>	<i>-0.50</i>	<i>1.59</i>	<i>2.05</i>
β_{INV}	-0.475	-0.500	-0.573	0.098	-0.581	-0.701	-0.317	0.263
t-stat	<i>-2.85</i>	<i>-2.46</i>	<i>-1.71</i>	<i>0.40</i>	<i>-2.16</i>	<i>-2.71</i>	<i>-1.95</i>	<i>0.92</i>
α_{both}	0.626	-0.061	-0.176	0.802	-0.058	0.143	0.535	0.593
t-stat	<i>2.26</i>	<i>-0.22</i>	<i>-0.48</i>	<i>2.81</i>	<i>-0.18</i>	<i>0.47</i>	<i>1.80</i>	<i>1.43</i>

Panel B. SEO: Equal-Weighted (I)CAPM Alphas

	MB1	MB2	MB3	3-1	Size1	Size2	Size3	1-3
α_{none}	-0.064	-0.308	-0.739	0.675	-0.572	-0.440	-0.240	0.331
t-stat	<i>-0.31</i>	<i>-1.47</i>	<i>-3.01</i>	<i>2.90</i>	<i>-2.44</i>	<i>-2.19</i>	<i>-1.74</i>	<i>1.36</i>
α_{BVIX}	-0.007	-0.194	-0.370	0.363	-0.299	-0.196	-0.243	0.056
t-stat	<i>-0.04</i>	<i>-0.93</i>	<i>-1.36</i>	<i>1.40</i>	<i>-1.14</i>	<i>-1.01</i>	<i>-1.67</i>	<i>0.19</i>
β_{BVIX}	-0.070	-0.126	-0.400	0.330	-0.292	-0.267	-0.010	0.282
t-stat	<i>-1.66</i>	<i>-2.66</i>	<i>-5.29</i>	<i>3.97</i>	<i>-3.69</i>	<i>-6.56</i>	<i>-0.13</i>	<i>2.03</i>
α_{INV}	0.210	-0.077	-0.428	0.638	-0.312	-0.018	-0.006	0.306
t-stat	<i>1.08</i>	<i>-0.40</i>	<i>-1.70</i>	<i>2.71</i>	<i>-1.28</i>	<i>-0.10</i>	<i>-0.05</i>	<i>1.12</i>
β_{INV}	-0.430	-0.362	-0.487	0.057	-0.407	-0.662	-0.367	0.040
t-stat	<i>-3.52</i>	<i>-2.98</i>	<i>-2.09</i>	<i>0.26</i>	<i>-2.16</i>	<i>-4.70</i>	<i>-4.95</i>	<i>0.18</i>
α_{both}	0.264	0.034	-0.066	0.330	-0.044	0.221	-0.010	0.034
t-stat	<i>1.34</i>	<i>0.17</i>	<i>-0.25</i>	<i>1.37</i>	<i>-0.17</i>	<i>1.17</i>	<i>-0.08</i>	<i>0.12</i>

Table 12. The Event-Time Regressions

The table presents the results of running the CAPM augmented by the BVIX, the investment factor, both, or none separately for six portfolios of new issues performed 2 to 7 months ago, 8 to 13 months ago, etc. The columns are named after the formation period interval. The alpha subscript in the rows shows the factor, with which I augment the CAPM. The sample period is from January 1986 to December 2001, January 2001 is excluded. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

	Panel A. IPO: EW (I)CAPM Alphas						Panel B. SEO: EW (I)CAPM Alphas					
	2-7	8-13	14-19	20-25	26-31	32-37	2-7	8-13	14-19	20-25	26-31	32-37
α_{none}	-0.642	-1.227	-1.169	-0.779	-0.571	0.223	-0.550	-0.998	-0.688	-0.544	-0.243	-0.147
t-stat	<i>-1.74</i>	<i>-3.39</i>	<i>-3.40</i>	<i>-2.60</i>	<i>-1.88</i>	<i>0.64</i>	<i>-2.61</i>	<i>-4.24</i>	<i>-3.23</i>	<i>-2.44</i>	<i>-1.01</i>	<i>-0.59</i>
α_{BVIX}	-0.345	-0.844	-0.874	-0.531	-0.333	0.505	-0.244	-0.763	-0.498	-0.329	-0.030	0.035
t-stat	<i>-0.98</i>	<i>-2.51</i>	<i>-2.58</i>	<i>-1.64</i>	<i>-1.03</i>	<i>1.31</i>	<i>-1.03</i>	<i>-3.28</i>	<i>-2.24</i>	<i>-1.47</i>	<i>-0.12</i>	<i>0.13</i>
β_{BVIX}	-0.348	-0.409	-0.333	-0.283	-0.293	-0.320	-0.332	-0.261	-0.199	-0.227	-0.236	-0.200
t-stat	<i>-1.70</i>	<i>-3.64</i>	<i>-5.35</i>	<i>-4.11</i>	<i>-4.12</i>	<i>-3.46</i>	<i>-3.06</i>	<i>-4.91</i>	<i>-3.39</i>	<i>-2.89</i>	<i>-3.92</i>	<i>-2.82</i>
α_{INV}	-0.345	-0.764	-0.696	-0.317	-0.217	0.500	-0.272	-0.633	-0.230	-0.064	0.105	-0.008
t-stat	<i>-0.82</i>	<i>-2.11</i>	<i>-2.09</i>	<i>-1.04</i>	<i>-0.68</i>	<i>1.42</i>	<i>-1.23</i>	<i>-3.04</i>	<i>-1.20</i>	<i>-0.30</i>	<i>0.49</i>	<i>-0.03</i>
β_{INV}	-0.466	-0.727	-0.742	-0.724	-0.555	-0.434	-0.436	-0.573	-0.718	-0.753	-0.546	-0.218
t-stat	<i>-1.28</i>	<i>-2.51</i>	<i>-3.27</i>	<i>-3.27</i>	<i>-2.28</i>	<i>-1.89</i>	<i>-2.08</i>	<i>-3.28</i>	<i>-5.29</i>	<i>-4.76</i>	<i>-3.38</i>	<i>-1.31</i>
α_{both}	-0.053	-0.388	-0.408	-0.075	0.016	0.777	0.028	-0.403	-0.045	0.146	0.313	0.171
t-stat	<i>-0.17</i>	<i>-1.29</i>	<i>-1.27</i>	<i>-0.23</i>	<i>0.05</i>	<i>2.03</i>	<i>0.13</i>	<i>-1.89</i>	<i>-0.23</i>	<i>0.63</i>	<i>1.38</i>	<i>0.70</i>

Table 13. Cumulative Issuance, Size, and Market-to-Book

Panel A presents the formation-year size and market-to-book across the cumulative issuance quintiles. The cumulative issuance is the log market value growth minus the cumulative log return in the past five years. The cumulative issuance portfolios are rebalanced annually in December. Size is the price times shares outstanding from CRSP, market-to-book is Compustat item #25 times item #199 divided by item #60 plus item #74. The Compustat items are measured prior to July of the formation year. Panel B shows the cumulative issuance in the 25 size - market-to-book portfolios. The breakpoints are determined using all CRSP/Compustat population. The portfolios are rebalanced annually in December. The sample includes 21 annual observations for 1985-2005. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

Panel A. Size and MB across Issuance Quintiles

	Low	Issue2	Issue3	Issue4	High	H-L
Size	2.535	2.519	1.514	1.487	1.057	-1.477
t-stat	<i>6.08</i>	<i>4.10</i>	<i>3.74</i>	<i>3.60</i>	<i>3.23</i>	<i>-3.95</i>
MB	2.501	2.114	2.976	4.196	5.425	2.924
t-stat	<i>11.24</i>	<i>15.60</i>	<i>4.63</i>	<i>7.42</i>	<i>21.62</i>	<i>9.98</i>

Panel B. Cumulative Issuance in Size - Market-to-Book Portfolios

	Small	Size2	Size3	Size4	Big	S-B
Low	0.104	0.079	0.112	0.069	0.005	0.099
t-stat	<i>5.4</i>	<i>3.8</i>	<i>5.3</i>	<i>3.8</i>	<i>0.1</i>	<i>3.1</i>
MB2	0.194	0.162	0.122	0.084	0.043	0.151
t-stat	<i>7.2</i>	<i>5.9</i>	<i>4.3</i>	<i>3.5</i>	<i>1.0</i>	<i>4.2</i>
MB3	0.309	0.262	0.170	0.124	0.031	0.278
t-stat	<i>8.0</i>	<i>9.4</i>	<i>9.0</i>	<i>5.8</i>	<i>1.1</i>	<i>12.1</i>
MB4	0.450	0.445	0.316	0.210	0.049	0.401
t-stat	<i>9.8</i>	<i>9.5</i>	<i>8.3</i>	<i>8.0</i>	<i>1.9</i>	<i>12.9</i>
High	0.662	0.721	0.563	0.354	0.074	0.588
t-stat	<i>16.8</i>	<i>18.8</i>	<i>11.8</i>	<i>14.7</i>	<i>2.9</i>	<i>23.0</i>
H-L	0.558	0.642	0.452	0.285	0.068	0.489
t(H-L)	<i>17.7</i>	<i>20.0</i>	<i>12.5</i>	<i>15.7</i>	<i>1.8</i>	<i>9.4</i>

Table 14. The Cumulative Issuance Puzzle, the BVIX Factor, and the Investment Factor

The table reports the results of fitting to the cumulative issuance arbitrage portfolio the ICAPM with the BVIX factor, the investment factor, or both. The cumulative issuance arbitrage portfolio is long in the top 30% issuance stocks and short in bottom 30% issuance stocks. The cumulative issuance is the log market value growth minus the cumulative log return in the past five years. The last row reports the percentage improvement after augmenting the CAPM with the factor(s). The right panel shows the results for the whole sample (February 1986 to December 2006), and the left panel removes January 2001. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

Panel A. Cum. Issuance: EW ICAPM Alphas							Panel B. Cum. Issuance: VW ICAPM Alphas					
	w/o January 2001			with January 2001			w/o January 2001			with January 2001		
	BVIX	INV	Both	BVIX	INV	Both	BVIX	INV	Both	BVIX	INV	Both
α	-0.410	-0.512	-0.204	-0.378	-0.347	-0.074	-0.499	-0.298	-0.189	-0.487	-0.250	-0.149
t-stat	<i>-1.43</i>	<i>-2.25</i>	<i>-0.85</i>	<i>-1.31</i>	<i>-1.38</i>	<i>-0.29</i>	<i>-3.04</i>	<i>-2.20</i>	<i>-1.32</i>	<i>-3.00</i>	<i>-1.91</i>	<i>-1.05</i>
β_{MKT}	0.415	0.402	0.349	0.441	0.386	0.341	0.373	0.294	0.274	0.383	0.289	0.272
t-stat	<i>7.26</i>	<i>4.52</i>	<i>5.38</i>	<i>6.11</i>	<i>4.29</i>	<i>5.12</i>	<i>8.98</i>	<i>5.74</i>	<i>6.99</i>	<i>7.98</i>	<i>5.72</i>	<i>6.89</i>
β_{BVIX}	-0.339		-0.338	-0.273		-0.277	-0.131		-0.129	-0.106		-0.110
t-stat	<i>-3.45</i>		<i>-3.11</i>	<i>-2.09</i>		<i>-1.99</i>	<i>-2.10</i>		<i>-1.69</i>	<i>-1.48</i>		<i>-1.34</i>
β_{INV}		-0.331	-0.324		-0.470	-0.483		-0.492	-0.490		-0.533	-0.538
t-stat		<i>-1.45</i>	<i>-1.81</i>		<i>-1.68</i>	<i>-1.92</i>		<i>-4.33</i>	<i>-5.10</i>		<i>-4.19</i>	<i>-4.69</i>
$\Delta\alpha/\alpha$	43%	29%	72%	41%	46%	88%	18%	51%	69%	16%	57%	74%

Table 15. The Cumulative Issuance Puzzle in Cross-Section

The table presents the results of estimating the CAPM augmented by the BVIX factor, the investment factor, both, or none for the cumulative issuance arbitrage portfolio in different size and market-to-book portfolios. The cumulative issuance arbitrage portfolio is long in the top 30% issuance stocks and short in bottom 30% issuance stocks. The cumulative issuance is the log market value growth minus the cumulative log return in the past five years. The size and market-to-book portfolios are the top 30%, the middle 40%, and the bottom 30%. Sorting on size is conditional on market-to-book. The alpha subscript in the rows shows the factor, with which I augment the CAPM. The sample period is from February 1986 to December 2001, January 2001 is excluded. The t-statistics use the Newey-West (1987) correction for autocorrelation and heteroscedasticity.

	MB1	MB2	MB3	1-3	Size1	Size2	Size3	3-1
α_{none}	0.035	-0.408	-1.148	1.183	-0.490	-0.970	-0.540	-0.050
t-stat	<i>0.15</i>	<i>-1.70</i>	<i>-2.71</i>	<i>4.29</i>	<i>-1.43</i>	<i>-3.61</i>	<i>-2.97</i>	<i>-0.19</i>
α_{BVIX}	0.200	-0.152	-0.493	0.693	-0.169	-0.638	-0.299	-0.130
t-stat	<i>0.83</i>	<i>-0.56</i>	<i>-0.93</i>	<i>1.79</i>	<i>-0.45</i>	<i>-2.09</i>	<i>-1.52</i>	<i>-0.47</i>
β_{BVIX}	-0.183	-0.280	-0.699	0.517	-0.361	-0.355	-0.254	0.107
t-stat	<i>-3.74</i>	<i>-3.54</i>	<i>-3.05</i>	<i>2.61</i>	<i>-3.12</i>	<i>-3.81</i>	<i>-4.79</i>	<i>1.30</i>
α_{INV}	0.181	-0.209	-1.005	1.186	-0.478	-0.783	-0.204	0.274
t-stat	<i>0.74</i>	<i>-1.01</i>	<i>-2.64</i>	<i>4.28</i>	<i>-1.40</i>	<i>-3.44</i>	<i>-1.31</i>	<i>0.99</i>
β_{INV}	-0.230	-0.312	-0.224	-0.006	-0.018	-0.293	-0.527	-0.509
t-stat	<i>-1.45</i>	<i>-1.47</i>	<i>-0.52</i>	<i>-0.02</i>	<i>-0.06</i>	<i>-1.28</i>	<i>-3.18</i>	<i>-3.37</i>
α_{both}	0.343	0.043	-0.359	0.702	-0.162	-0.456	0.032	0.194
t-stat	<i>1.38</i>	<i>0.19</i>	<i>-0.84</i>	<i>2.22</i>	<i>-0.46</i>	<i>-1.80</i>	<i>0.18</i>	<i>0.70</i>

Table 16. Robustness: Revisiting Bali and Cakici (2007)

In this table I look at equal-weighted Fama-French alphas of idiosyncratic volatility quintiles formed using NYSE only firms. Panel A uses the daily measure of idiosyncratic volatility, and Panel B uses the monthly measure. Idiosyncratic volatility is the standard deviation of Fama-French residuals. For the daily measure, in each firm-month with at least 15 valid observations I fit the model to daily returns. For the monthly measure, I fit the model to monthly returns over the previous 60 months (at least 24 valid observations required). I first classify firms as NYSE using the current listing, `hexcd` from the CRSP returns file, to mimic Bali and Cakici (2007). Then I add the delisting returns, and then use the listing at the portfolio formation date, `exchcd` from the CRSP events file. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2004.

Panel A. Daily Volatility, NYSE Only							Panel B. Monthly Volatility, NYSE Only						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Raw_{hexcd}	1.162	1.404	1.539	1.614	1.415	-0.253	Raw_{hexcd}	1.164	1.324	1.435	1.467	1.672	-0.508
t-stat	<i>6.21</i>	<i>6.32</i>	<i>6.09</i>	<i>5.42</i>	<i>3.86</i>	<i>-1.08</i>	t-stat	<i>6.72</i>	<i>6.22</i>	<i>5.61</i>	<i>4.87</i>	<i>4.45</i>	<i>-1.87</i>
α_{hexcd}	0.060	0.182	0.225	0.181	-0.260	0.319	α_{hexcd}	0.079	0.111	0.072	-0.001	0.045	0.034
t-stat	<i>0.86</i>	<i>2.49</i>	<i>2.62</i>	<i>1.95</i>	<i>-2.20</i>	<i>2.67</i>	t-stat	<i>1.14</i>	<i>1.58</i>	<i>0.86</i>	<i>-0.01</i>	<i>0.38</i>	<i>0.27</i>
$\alpha_{+\text{Delist}}$	0.063	0.183	0.227	0.182	-0.286	0.349	$\alpha_{+\text{Delist}}$	0.080	0.112	0.076	-0.003	-0.057	0.137
t-stat	<i>0.91</i>	<i>2.50</i>	<i>2.64</i>	<i>1.96</i>	<i>-2.42</i>	<i>2.91</i>	t-stat	<i>1.16</i>	<i>1.60</i>	<i>0.91</i>	<i>-0.03</i>	<i>-0.47</i>	<i>1.07</i>
α_{exchcd}	0.000	0.113	0.099	0.007	-0.850	0.849	α_{exchcd}	0.063	0.049	0.004	-0.134	-0.605	0.668
t-stat	<i>-0.01</i>	<i>1.66</i>	<i>1.23</i>	<i>0.08</i>	<i>-6.89</i>	<i>6.30</i>	t-stat	<i>0.91</i>	<i>0.72</i>	<i>0.05</i>	<i>-1.44</i>	<i>-5.00</i>	<i>4.87</i>

Table 17. Leverage: Portfolio Tests

The table presents the idiosyncratic volatility discount across the leverage and the O-score quintiles formed using NYSE (`exchcd=1`) breakpoints. Leverage is the sum of short-term (Compustat item #9) and long-term debt (Compustat item #34) over the market value of equity (item #25 times item #199). O is the O-score is defined in (25). The idiosyncratic volatility discount is defined as the difference in value-weighted abnormal returns between extreme idiosyncratic volatility quintiles. I form the quintiles using NYSE (`exchcd=1`) breakpoints. The abnormal returns are from the CAPM, the Fama-French model (FF), and the ICAPM with BVIX. For the ICAPM, I also report the BVIX betas. The BVIX factor is defined in the heading of Table 4. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006 for the CAPM and the FF model, and from February 1986 to December 2006 for the ICAPM.

Panel A. IVol Discount and Leverage

	Lev 1	Lev 2	Lev 3	Lev 4	Lev 5	5-1
α_{CAPM}	0.684	0.625	0.617	0.476	0.454	-0.229
t-stat	<i>2.87</i>	<i>2.85</i>	<i>2.47</i>	<i>1.89</i>	<i>1.88</i>	<i>-0.89</i>
α_{FF}	0.555	0.595	0.642	0.517	0.691	0.136
t-stat	<i>2.70</i>	<i>3.31</i>	<i>3.24</i>	<i>2.50</i>	<i>3.48</i>	<i>0.57</i>
α_{ICAPM}	0.189	0.376	0.463	0.414	0.140	-0.049
t-stat	<i>0.45</i>	<i>1.02</i>	<i>1.11</i>	<i>1.07</i>	<i>0.45</i>	<i>-0.11</i>
β_{BVIX}	0.616	0.313	0.244	0.503	0.031	-0.585
t-stat	<i>3.42</i>	<i>2.14</i>	<i>2.31</i>	<i>3.39</i>	<i>0.32</i>	<i>-3.16</i>

Panel B. IVol Discount and O-Score

VW	O 1	O 2	O 3	O 4	O 5	5-1
α_{CAPM}	0.821	0.518	0.567	0.460	0.803	-0.017
t-stat	<i>3.01</i>	<i>1.92</i>	<i>2.53</i>	<i>2.27</i>	<i>3.29</i>	<i>-0.07</i>
α_{FF}	0.551	0.402	0.546	0.382	0.804	0.254
t-stat	<i>2.59</i>	<i>1.99</i>	<i>2.75</i>	<i>1.96</i>	<i>3.73</i>	<i>0.99</i>
α_{ICAPM}	0.287	0.171	0.371	0.008	0.664	0.377
t-stat	<i>0.60</i>	<i>0.38</i>	<i>0.89</i>	<i>0.02</i>	<i>1.69</i>	<i>1.02</i>
β_{BVIX}	0.672	0.677	0.568	0.404	0.350	-0.322
t-stat	<i>3.41</i>	<i>3.55</i>	<i>2.87</i>	<i>2.80</i>	<i>2.55</i>	<i>-2.45</i>

Table 18. Leverage: Cross-Sectional Tests

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw return. All variables except for beta are percentage rankings. The variables themselves are described in the heading of Table 2 and Table 17. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2006.

	1	2	3	4	5	6	7	8
Beta	0.341	0.342	0.344	0.339	0.341	0.340	0.342	0.345
t-stat	<i>6.97</i>	<i>6.99</i>	<i>7.03</i>	<i>6.89</i>	<i>6.94</i>	<i>6.91</i>	<i>6.97</i>	<i>7.02</i>
Size	-0.0146	-0.0146	-0.0155	-0.0140	-0.0139	-0.0141	-0.0149	-0.0149
t-stat	<i>-4.90</i>	<i>-4.89</i>	<i>-5.19</i>	<i>-4.75</i>	<i>-4.72</i>	<i>-4.76</i>	<i>-5.01</i>	<i>-5.02</i>
MB	-0.0113	-0.0113	0.0055	-0.0093	-0.0117	-0.0093	0.0056	0.0051
t-stat	<i>-4.97</i>	<i>-4.98</i>	<i>1.99</i>	<i>-3.96</i>	<i>-5.36</i>	<i>-4.01</i>	<i>2.10</i>	<i>1.87</i>
IVol	-0.0095	-0.0113	0.0088	-0.0098	-0.0096	-0.0079	0.0050	0.0095
t-stat	<i>-3.15</i>	<i>-2.75</i>	<i>2.12</i>	<i>-3.20</i>	<i>-3.22</i>	<i>-2.00</i>	<i>1.28</i>	<i>1.97</i>
Lev	-0.0045	-0.0063	0.0013		-0.0049			-0.0007
t-stat	<i>-2.42</i>	<i>-3.76</i>	<i>0.78</i>		<i>-2.67</i>			<i>-0.42</i>
O-Score				-0.0045	-0.0044	-0.0021	-0.0016	-0.0021
t-stat				<i>-4.17</i>	<i>-4.35</i>	<i>-1.24</i>	<i>-0.90</i>	<i>-1.21</i>
IVol*		0.00003	-0.00010					-0.00007
*Lev		<i>1.07</i>	<i>-3.24</i>					<i>-2.31</i>
IVol*						-0.00004	-0.00006	-0.00005
*O-score						<i>-1.21</i>	<i>-1.77</i>	<i>-1.44</i>
IVol*			-0.00028				-0.00026	-0.00029
MB			<i>-7.24</i>				<i>-6.62</i>	<i>-7.09</i>

Table 19. The Investment Anomaly and Idiosyncratic Volatility

The table presents the investment anomaly across the idiosyncratic volatility quintiles. The investment anomaly is defined as the value-weighted return differential between the lowest and the highest investment quintiles. Both the investment and the idiosyncratic volatility quintiles are formed using NYSE (`exchcd=1`) breakpoints. In Panel A investment is defined as the change in the capital expenditure (Compustat item #128) compared to the previous year over the previous year CAPEX. In Panel B investment is the change in gross PPE (item #7) over total assets (item #6). In Panel C investment is the change in gross PPE plus the change in inventories (item #3) over total assets. The abnormal returns are from the CAPM, the Fama-French model (FF), and the ICAPM with BVIX. For the ICAPM, I also report the BVIX betas. The BVIX factor is defined in the heading of Table 4. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from February 1986 to December 2006.

Panel A. Investment Growth

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
α_{CAPM}	0.166	0.329	0.626	0.301	0.776	0.610
t-stat	<i>0.63</i>	<i>1.10</i>	<i>2.07</i>	<i>0.98</i>	<i>2.79</i>	<i>1.52</i>
α_{FF}	0.063	0.097	0.435	0.016	0.428	0.365
t-stat	<i>0.21</i>	<i>0.29</i>	<i>1.40</i>	<i>0.06</i>	<i>1.89</i>	<i>0.97</i>
α_{ICAPM}	0.167	0.360	0.818	0.321	0.734	0.567
t-stat	<i>0.65</i>	<i>1.23</i>	<i>2.60</i>	<i>0.87</i>	<i>2.63</i>	<i>1.52</i>
β_{BVIX}	-0.005	-0.032	-0.191	-0.026	0.035	0.040
t-stat	<i>-0.08</i>	<i>-0.26</i>	<i>-1.56</i>	<i>-0.21</i>	<i>0.44</i>	<i>0.40</i>

Panel B. Investment (excl. inventories) over Total Assets

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
α_{CAPM}	-0.103	0.407	0.237	0.274	0.701	0.805
t-stat	<i>-0.36</i>	<i>1.74</i>	<i>1.04</i>	<i>1.03</i>	<i>1.99</i>	<i>1.72</i>
α_{FF}	-0.209	0.190	0.085	0.018	0.153	0.362
t-stat	<i>-0.65</i>	<i>0.76</i>	<i>0.38</i>	<i>0.07</i>	<i>0.61</i>	<i>0.86</i>
α_{ICAPM}	0.138	0.485	0.172	0.195	0.556	0.418
t-stat	<i>0.49</i>	<i>2.03</i>	<i>0.77</i>	<i>0.68</i>	<i>1.72</i>	<i>0.99</i>
β_{BVIX}	-0.262	-0.084	0.055	0.095	0.137	0.399
t-stat	<i>-2.42</i>	<i>-0.76</i>	<i>0.60</i>	<i>1.12</i>	<i>1.42</i>	<i>3.52</i>

Panel C. Investment (incl. inventories) over Total Assets

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
α_{CAPM}	-0.188	0.425	0.030	0.714	0.905	1.092
t-stat	<i>-0.69</i>	<i>1.68</i>	<i>0.13</i>	<i>2.22</i>	<i>2.54</i>	<i>2.44</i>
α_{FF}	-0.323	0.162	-0.128	0.392	0.412	0.735
t-stat	<i>-1.09</i>	<i>0.60</i>	<i>-0.53</i>	<i>1.26</i>	<i>1.56</i>	<i>1.80</i>
α_{ICAPM}	-0.008	0.582	-0.054	0.673	0.802	0.810
t-stat	<i>-0.03</i>	<i>2.16</i>	<i>-0.22</i>	<i>1.97</i>	<i>2.42</i>	<i>1.92</i>
β_{BVIX}	-0.199	-0.137	0.083	0.053	0.101	0.300
t-stat	<i>-2.00</i>	<i>-1.25</i>	<i>0.97</i>	<i>0.62</i>	<i>1.21</i>	<i>2.59</i>

Table 20. Investment and the Idiosyncratic Volatility Discount

The table presents the idiosyncratic volatility discount across the investment quintiles. The idiosyncratic volatility discount is defined as the value-weighted return differential between the lowest and the highest idiosyncratic volatility quintiles. Both the investment and the idiosyncratic volatility quintiles are formed using NYSE (`exchcd=1`) breakpoints. In Panel A investment is defined as the change in the capital expenditure (Compustat item #128) compared to the previous year over the previous year CAPEX. In Panel B investment is the change in gross PPE (item #7) over total assets (item #6). In Panel C investment is the change in gross PPE plus the change in inventories (item #3) over total assets. The abnormal returns are from the CAPM, the Fama-French model (FF), and the ICAPM with BVIX. For the ICAPM, I also report the BVIX betas. The BVIX factor is defined in the heading of Table 4. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from February 1986 to December 2006.

Panel A. Investment Growth

	Inv 1	Inv 2	Inv 3	Inv 4	Inv 5	5-1
α_{CAPM}	0.599	0.390	0.333	0.518	1.208	0.610
t-stat	<i>1.83</i>	<i>1.20</i>	<i>0.86</i>	<i>1.57</i>	<i>2.45</i>	<i>1.52</i>
α_{FF}	0.228	0.278	0.000	0.273	0.592	0.365
t-stat	<i>1.01</i>	<i>1.08</i>	<i>0.00</i>	<i>0.95</i>	<i>1.45</i>	<i>0.97</i>
α_{ICAPM}	0.070	0.042	-0.039	-0.012	0.637	0.567
t-stat	<i>0.20</i>	<i>0.13</i>	<i>-0.09</i>	<i>-0.03</i>	<i>1.37</i>	<i>1.52</i>
β_{BVIX}	0.535	0.344	0.372	0.548	0.575	0.040
t-stat	<i>3.36</i>	<i>3.43</i>	<i>2.02</i>	<i>4.25</i>	<i>2.76</i>	<i>0.40</i>

Panel B. Investment (excl. inventories) over Total Assets

	Inv 1	Inv 2	Inv 3	Inv 4	Inv 5	5-1
α_{CAPM}	0.309	0.435	0.846	0.793	1.113	0.805
t-stat	<i>0.90</i>	<i>1.43</i>	<i>2.38</i>	<i>2.29</i>	<i>2.43</i>	<i>1.72</i>
α_{FF}	0.215	0.346	0.402	0.378	0.577	0.362
t-stat	<i>0.73</i>	<i>1.38</i>	<i>1.32</i>	<i>1.47</i>	<i>1.59</i>	<i>0.86</i>
α_{ICAPM}	-0.006	-0.045	0.346	0.358	0.412	0.418
t-stat	<i>-0.02</i>	<i>-0.14</i>	<i>0.93</i>	<i>0.96</i>	<i>0.84</i>	<i>0.99</i>
β_{BVIX}	0.315	0.499	0.505	0.444	0.714	0.399
t-stat	<i>1.66</i>	<i>4.39</i>	<i>3.32</i>	<i>3.00</i>	<i>4.19</i>	<i>3.52</i>

Panel C. Investment (incl. inventories) over Total Assets

	Inv 1	Inv 2	Inv 3	Inv 4	Inv 5	5-1
α_{CAPM}	0.157	0.484	0.686	0.574	1.250	1.092
t-stat	<i>0.47</i>	<i>1.55</i>	<i>1.78</i>	<i>1.62</i>	<i>2.85</i>	<i>2.44</i>
α_{FF}	0.071	0.345	0.218	0.094	0.806	0.735
t-stat	<i>0.24</i>	<i>1.16</i>	<i>0.72</i>	<i>0.33</i>	<i>2.26</i>	<i>1.80</i>
α_{ICAPM}	-0.221	0.000	0.296	0.015	0.589	0.810
t-stat	<i>-0.62</i>	<i>0.00</i>	<i>0.76</i>	<i>0.04</i>	<i>1.24</i>	<i>1.92</i>
β_{BVIX}	0.380	0.496	0.386	0.562	0.680	0.300
t-stat	<i>1.99</i>	<i>4.19</i>	<i>3.06</i>	<i>2.29</i>	<i>3.92</i>	<i>2.59</i>

Table 21. BVIX Factor and Anomalies: Robustness

The table presents the ICAPM alphas and BVIX betas using alternative definitions of the BVIX factor. The "1 month" column employs the BVIX index used throughout the paper: the stocks are sorted on the previous month return sensitivity to VIX changes and the hedge portfolio goes long in the most negative and short in the most positive return sensitivity portfolios held for one month. In the "2-12 months" column BVIX is formed using the portfolios sorted on the previous month return sensitivity and held for eleven months skipping the month after formation. In the "1 year" column BVIX is formed using the same portfolios held for twelve months without skipping the month. In the "annual" column BVIX is formed using portfolios sorted based on the previous year return sensitivity and held for one year after.

The anomalous portfolios in Panel A are the four portfolios defined in the heading of Table 6. Panel B looks at the smallest and second smallest growth portfolios from the Fama and French (1992) size - book-to-market sorts, both equal-weighted and value-weighted (e.g., SG2VW is the value-weighted second smallest growth portfolio). Panel C looks at the IPO and SEO portfolios (see the heading of Table 9) and the cumulative issuance hedging portfolio (see the heading of Table 14).

Panel A. IVol Discount and Market-to-Book

	1 month		1 year		2-12 months		Annual	
	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}
IVol	0.421	0.533	0.333	1.405	0.426	1.293	0.453	0.640
t-stat	<i>1.25</i>	<i>3.26</i>	<i>1.18</i>	<i>7.90</i>	<i>1.52</i>	<i>8.73</i>	<i>1.61</i>	<i>7.15</i>
IVolh	0.544	0.604	0.455	1.580	0.555	1.463	0.582	0.731
t-stat	<i>1.38</i>	<i>3.57</i>	<i>1.31</i>	<i>7.28</i>	<i>1.61</i>	<i>7.98</i>	<i>1.65</i>	<i>7.92</i>
HMLh	0.954	0.382	1.124	0.456	1.190	0.344	1.138	0.315
t-stat	<i>2.58</i>	<i>2.75</i>	<i>2.87</i>	<i>1.72</i>	<i>3.02</i>	<i>1.42</i>	<i>3.08</i>	<i>2.71</i>
IVol55	-0.443	-0.395	-0.407	-0.976	-0.464	-0.896	-0.446	-0.476
t-stat	<i>-1.43</i>	<i>-2.94</i>	<i>-1.54</i>	<i>-4.69</i>	<i>-1.76</i>	<i>-4.95</i>	<i>-1.63</i>	<i>-5.75</i>

Panel B. Small Growth Anomaly

	1 month		1 year		2-12 months		Annual	
	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}
SG1VW	-0.461	-0.568	-0.543	-0.934	-0.684	-0.788	-0.617	-0.459
t-stat	<i>-1.00</i>	<i>-2.49</i>	<i>-1.35</i>	<i>-2.76</i>	<i>-1.89</i>	<i>-2.98</i>	<i>-1.51</i>	<i>-2.42</i>
SG2VW	-0.166	-0.408	-0.249	-0.624	-0.342	-0.529	-0.270	-0.344
t-stat	<i>-0.56</i>	<i>-2.55</i>	<i>-0.97</i>	<i>-2.38</i>	<i>-1.47</i>	<i>-2.52</i>	<i>-1.02</i>	<i>-2.54</i>
SG1EW	-0.417	-0.462	-0.327	-1.032	-0.486	-0.924	-0.467	-0.433
t-stat	<i>-0.88</i>	<i>-2.98</i>	<i>-0.72</i>	<i>-4.14</i>	<i>-1.14</i>	<i>-4.39</i>	<i>-1.05</i>	<i>-3.55</i>
SG2EW	-0.413	-0.353	-0.360	-0.805	-0.450	-0.743	-0.462	-0.347
t-stat	<i>-1.57</i>	<i>-3.78</i>	<i>-1.46</i>	<i>-3.92</i>	<i>-1.93</i>	<i>-4.08</i>	<i>-1.92</i>	<i>-4.12</i>

Panel C. New Issues Puzzle

	1 month		1 year		2-12 months		Annual	
	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}	α_{ICAPM}	β_{BVIX}
IPO	-0.308	-0.376	-0.161	-1.115	-0.243	-1.055	-0.323	-0.452
t-stat	<i>-0.96</i>	<i>-4.39</i>	<i>-0.56</i>	<i>-5.74</i>	<i>-0.85</i>	<i>-5.70</i>	<i>-1.16</i>	<i>-6.62</i>
SEO	-0.237	-0.257	-0.202	-0.618	-0.252	-0.574	-0.290	-0.254
t-stat	<i>-1.16</i>	<i>-6.01</i>	<i>-0.96</i>	<i>-3.89</i>	<i>-1.19</i>	<i>-3.72</i>	<i>-1.42</i>	<i>-5.19</i>
CumIss	0.347	0.340	0.324	0.768	0.395	0.692	0.414	0.341
t-stat	<i>1.18</i>	<i>3.45</i>	<i>1.24</i>	<i>5.56</i>	<i>1.56</i>	<i>5.89</i>	<i>1.61</i>	<i>4.73</i>

Table 22. Behavioral Stories: Characteristic-Based Tests

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw return. RInst is the percentage rank of previous quarter residual institutional ownership less 100. Residual institutional ownership is defined as the residual from the logistic regression (19) of institutional ownership on log size and its square. Short is the percentage rank of probability to be on special defined in (20) and (21). All other variables are described in the heading of Table 2. The sample excludes all stocks below the 20th NYSE/AMEX size percentile at the date of the institutional ownership measurement. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from April 1980 to December 2006.

Panel A. Residual Institutional Ownership						Panel B. Probability on Special					
	1	2	3	4	5		1	2	3	4	5
Beta	0.271	0.279	0.280	0.281	0.280	Beta	0.290	0.295	0.298	0.300	0.300
t-stat	<i>4.50</i>	<i>4.67</i>	<i>4.71</i>	<i>4.74</i>	<i>4.71</i>	t-stat	<i>4.49</i>	<i>4.62</i>	<i>4.66</i>	<i>4.68</i>	<i>4.70</i>
Size	-0.0113	-0.0111	-0.0116	-0.0122	-0.0127	Size	-0.0122	-0.0293	-0.0282	-0.0273	-0.0275
t-stat	<i>-2.72</i>	<i>-2.68</i>	<i>-2.80</i>	<i>-2.96</i>	<i>-3.06</i>	t-stat	<i>-2.79</i>	<i>-5.38</i>	<i>-5.19</i>	<i>-5.10</i>	<i>-5.09</i>
MB	-0.0076	-0.0066	-0.0062	0.0060	0.0054	MB	-0.0070	-0.0038	-0.0030	0.0107	0.0086
t-stat	<i>-2.13</i>	<i>-1.92</i>	<i>-1.79</i>	<i>1.70</i>	<i>1.56</i>	t-stat	<i>-2.02</i>	<i>-1.14</i>	<i>-0.92</i>	<i>2.71</i>	<i>2.27</i>
IVol	-0.0173	-0.0166	-0.0040	0.0081	0.0006	IVol	-0.0166	-0.0140	0.0025	0.0166	0.0075
t-stat	<i>-3.93</i>	<i>-3.84</i>	<i>-1.02</i>	<i>2.00</i>	<i>0.17</i>	t-stat	<i>-3.75</i>	<i>-3.48</i>	<i>0.57</i>	<i>3.24</i>	<i>1.20</i>
RInst		0.0051	-0.0081	-0.0069	-0.0063	Short		-0.0137	0.0014	0.0016	0.0012
t-stat		<i>3.43</i>	<i>-4.88</i>	<i>-4.58</i>	<i>-4.14</i>	t-stat		<i>-4.30</i>	<i>0.43</i>	<i>0.49</i>	<i>0.36</i>
IVol*			0.00027	0.00024	0.00009	IVol*			-0.00032	-0.00029	-0.00017
*RInst			<i>5.77</i>	<i>5.52</i>	<i>1.61</i>	*Short			<i>-4.51</i>	<i>-4.23</i>	<i>-1.74</i>
IVol*				-0.00025	-0.00012	IVol*				-0.00028	-0.00014
*MB				<i>-4.58</i>	<i>-1.87</i>	*MB				<i>-4.57</i>	<i>-1.44</i>
IVol*					0.000003	IVol*					-0.000002
MB					<i>4.21</i>	*MB*					<i>-1.92</i>
*Rinst						*Short					

Table 23. Behavioral Stories: Covariance-Based Tests

The table presents the idiosyncratic volatility discount across the limits-to-arbitrage quintiles formed using NYSE (`exchcd=1`) breakpoints. RI is residual institutional ownership, defined as the residual from the logistic regression (19) of institutional ownership on log size and its square. Sh is the probability to be on special, defined in (20) and (21). The idiosyncratic volatility discount is defined as the difference in value-weighted abnormal returns between extreme idiosyncratic volatility quintiles. I form the quintiles using NYSE (`exchcd=1`) breakpoints. The abnormal returns are from the CAPM, the Fama-French model (FF), and the ICAPM with BVIX. For the ICAPM, I also report the BVIX betas. The BVIX factor is defined in the heading of Table 4. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from February 1986 to December 2006.

Panel A. Residual Institutional Ownership

	Low	RI 2	RI 3	RI 4	High	L-H
α_{CAPM}	1.364	0.982	0.456	0.372	0.570	0.795
t-stat	<i>3.11</i>	<i>2.53</i>	<i>1.48</i>	<i>1.24</i>	<i>1.54</i>	<i>1.83</i>
α_{FF}	0.722	0.479	0.069	-0.006	0.424	0.299
t-stat	<i>2.23</i>	<i>1.55</i>	<i>0.28</i>	<i>-0.03</i>	<i>1.40</i>	<i>0.77</i>
α_{ICAPM}	0.807	0.532	0.018	-0.156	0.064	0.744
t-stat	<i>2.00</i>	<i>1.36</i>	<i>0.05</i>	<i>-0.48</i>	<i>0.15</i>	<i>1.84</i>
β_{BVIX}	0.568	0.459	0.447	0.537	0.516	0.052
t-stat	<i>2.47</i>	<i>2.65</i>	<i>3.23</i>	<i>4.27</i>	<i>3.73</i>	<i>0.35</i>

Panel B. Probability on Special

	Low	Sh 2	Sh 3	Sh 4	High	H-L
α_{CAPM}	0.370	0.726	0.891	0.854	1.054	0.684
t-stat	<i>1.14</i>	<i>2.07</i>	<i>2.36</i>	<i>1.87</i>	<i>2.07</i>	<i>1.69</i>
α_{FF}	0.039	0.316	0.325	0.204	0.151	0.111
t-stat	<i>0.14</i>	<i>1.15</i>	<i>1.21</i>	<i>0.61</i>	<i>0.49</i>	<i>0.32</i>
α_{ICAPM}	0.082	0.218	0.284	0.234	0.384	0.302
t-stat	<i>0.25</i>	<i>0.60</i>	<i>0.71</i>	<i>0.48</i>	<i>0.68</i>	<i>0.66</i>
β_{BVIX}	0.294	0.517	0.618	0.631	0.683	0.389
t-stat	<i>3.23</i>	<i>3.49</i>	<i>3.08</i>	<i>2.90</i>	<i>2.36</i>	<i>1.52</i>

Table 24. Announcement Returns

The table presents returns to the 25 volatility - market-to-book portfolios measured over the next quarter after forming the portfolios on idiosyncratic volatility. In each month, stocks are sorted into quartiles based on the previous month volatility, and a volatility portfolio in each month consists of three equally-weighted portfolios - formed 3, 2, and 1 months ago. Panel A presents the announcement returns measured as the cumulative return in the three trading days around an earnings announcement. I divide the announcement return by 3 to make it comparable to the raw monthly returns in Panel B. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from July 1971 to December 2006.

Panel A. Announcement Value-Weighted Returns							Panel B. Raw Value-Weighted Returns						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	0.197	0.202	0.202	0.173	0.177	0.020	Value	1.400	1.497	1.668	1.578	1.389	0.011
t-stat	<i>5.20</i>	<i>5.26</i>	<i>5.35</i>	<i>3.96</i>	<i>3.45</i>	<i>0.31</i>	t-stat	<i>6.29</i>	<i>5.96</i>	<i>5.58</i>	<i>4.67</i>	<i>3.31</i>	<i>0.03</i>
mb2	0.145	0.169	0.124	0.165	0.120	0.025	mb2	1.293	1.220	1.378	1.338	0.829	0.464
t-stat	<i>3.88</i>	<i>5.31</i>	<i>4.05</i>	<i>4.28</i>	<i>2.75</i>	<i>0.46</i>	t-stat	<i>6.24</i>	<i>5.13</i>	<i>5.02</i>	<i>4.14</i>	<i>2.22</i>	<i>1.45</i>
mb3	0.141	0.128	0.141	0.111	0.077	0.064	mb3	1.184	1.105	1.326	1.076	0.772	0.412
t-stat	<i>4.64</i>	<i>4.63</i>	<i>4.78</i>	<i>2.76</i>	<i>1.58</i>	<i>1.17</i>	t-stat	<i>5.97</i>	<i>5.17</i>	<i>4.73</i>	<i>3.31</i>	<i>2.03</i>	<i>1.25</i>
mb4	0.086	0.144	0.148	0.071	-0.018	0.103	mb4	1.070	1.101	1.041	0.971	0.416	0.654
t-stat	<i>3.41</i>	<i>4.98</i>	<i>4.21</i>	<i>1.79</i>	<i>-0.33</i>	<i>1.79</i>	t-stat	<i>5.01</i>	<i>4.72</i>	<i>3.80</i>	<i>2.62</i>	<i>1.02</i>	<i>1.92</i>
Growth	0.088	0.114	0.085	0.050	-0.122	0.210	Growth	1.015	0.989	0.934	0.709	-0.229	1.244
t-stat	<i>2.65</i>	<i>3.12</i>	<i>2.24</i>	<i>1.12</i>	<i>-2.11</i>	<i>3.24</i>	t-stat	<i>4.32</i>	<i>3.83</i>	<i>2.86</i>	<i>1.76</i>	<i>-0.50</i>	<i>3.36</i>
V-G	0.109	0.088	0.117	0.123	0.299	0.190	V-G	0.385	0.509	0.733	0.869	1.618	1.233
t(V-G)	<i>2.26</i>	<i>1.94</i>	<i>2.17</i>	<i>1.93</i>	<i>4.10</i>	<i>2.22</i>	t(V-G)	<i>1.58</i>	<i>2.14</i>	<i>2.89</i>	<i>3.05</i>	<i>4.90</i>	<i>3.78</i>

Panel C. Month before earnings announcement							Panel D. Month after earnings announcement						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	1.103	1.673	1.830	2.367	2.925	-1.822	Value	1.612	1.314	1.658	1.628	1.515	0.097
t-stat	<i>3.82</i>	<i>5.34</i>	<i>5.28</i>	<i>5.74</i>	<i>6.29</i>	<i>-4.26</i>	t-stat	<i>5.67</i>	<i>4.88</i>	<i>5.69</i>	<i>4.35</i>	<i>3.24</i>	<i>0.20</i>
mb2	1.118	0.936	1.278	1.582	2.267	-1.149	mb2	1.326	1.618	1.602	1.520	1.093	0.233
t-stat	<i>4.28</i>	<i>3.08</i>	<i>3.67</i>	<i>4.24</i>	<i>4.67</i>	<i>-2.93</i>	t-stat	<i>5.53</i>	<i>6.59</i>	<i>6.39</i>	<i>4.34</i>	<i>2.68</i>	<i>0.62</i>
mb3	1.017	0.988	1.408	1.707	2.379	-1.361	mb3	1.632	1.406	1.289	1.278	0.880	0.753
t-stat	<i>4.44</i>	<i>3.82</i>	<i>4.71</i>	<i>4.34</i>	<i>4.74</i>	<i>-3.11</i>	t-stat	<i>7.30</i>	<i>5.78</i>	<i>4.68</i>	<i>3.88</i>	<i>2.09</i>	<i>1.94</i>
mb4	0.780	0.784	1.082	1.419	1.484	-0.704	mb4	1.286	1.337	1.174	1.169	0.734	0.552
t-stat	<i>2.95</i>	<i>2.89</i>	<i>3.31</i>	<i>3.29</i>	<i>2.71</i>	<i>-1.43</i>	t-stat	<i>5.16</i>	<i>5.93</i>	<i>4.11</i>	<i>3.43</i>	<i>1.71</i>	<i>1.32</i>
Growth	0.730	0.850	1.018	1.085	0.885	-0.155	Growth	1.453	1.210	1.317	1.192	0.402	1.052
t-stat	<i>2.37</i>	<i>2.81</i>	<i>2.79</i>	<i>2.42</i>	<i>1.64</i>	<i>-0.30</i>	t-stat	<i>5.29</i>	<i>4.43</i>	<i>3.92</i>	<i>3.03</i>	<i>0.76</i>	<i>2.24</i>
V-G	0.374	0.823	0.812	1.282	2.040	1.667	V-G	0.158	0.104	0.341	0.436	1.114	0.955
t(V-G)	<i>1.14</i>	<i>2.48</i>	<i>2.70</i>	<i>3.83</i>	<i>4.68</i>	<i>3.28</i>	t(V-G)	<i>0.48</i>	<i>0.35</i>	<i>1.08</i>	<i>1.26</i>	<i>2.45</i>	<i>1.89</i>

Table 25. Betas Changes around Earnings Announcements

The table presents the changes in betas around earnings announcements. The betas are estimated from the regressions fitted to daily data 30 calendar days prior to an earnings announcement, ending two trading days before it, and 30 calendar days after an earnings announcement, starting two trading days after it. The difference in the betas estimates is reported in the table. The market beta and the BVIX beta in Panels A and B are estimated from the ICAPM with the BVIX, and the SMB and HML betas in Panels C and D are estimated from the Fama-French model. The portfolios are formed each month and held for the next quarter, as described in the heading of Table 24. The t-statistics reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Changes in the Market Betas							Panel B. Changes in the VIX Betas						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	0.010	0.022	-0.038	-0.014	0.023	-0.012	Value	-0.013	-0.032	-0.032	-0.004	-0.023	0.010
t-stat	0.44	0.90	-1.45	-0.59	0.95	-0.34	t-stat	-0.31	-0.78	-0.82	-0.12	-0.67	0.19
mb2	0.036	-0.005	-0.003	-0.047	-0.040	0.075	mb2	0.000	-0.042	-0.031	0.020	-0.007	0.006
t-stat	1.39	-0.18	-0.10	-2.01	-1.59	2.19	t-stat	-0.01	-1.14	-0.82	0.54	-0.20	0.14
mb3	0.009	-0.007	0.006	0.006	-0.033	0.042	mb3	0.027	0.024	0.069	0.053	0.076	-0.048
t-stat	0.38	-0.35	0.28	0.24	-1.40	1.31	t-stat	0.75	0.71	2.29	1.72	1.92	-1.02
mb4	-0.035	-0.032	-0.060	-0.025	-0.004	-0.031	mb4	0.016	0.014	-0.014	-0.024	0.010	0.006
t-stat	-1.47	-1.83	-2.48	-1.01	-0.18	-0.93	t-stat	0.44	0.44	-0.52	-0.69	0.26	0.12
Growth	-0.014	-0.014	-0.030	-0.034	-0.089	0.075	Growth	-0.006	0.010	-0.033	-0.002	0.028	-0.034
t-stat	-0.63	-0.62	-1.39	-1.86	-3.01	1.83	t-stat	-0.21	0.34	-1.06	-0.07	0.78	-0.75
V-G	0.024	0.036	-0.008	0.020	0.112	0.087	V-G	-0.007	-0.042	0.001	-0.002	-0.051	-0.044
t(V-G)	0.73	1.27	-0.25	0.63	3.09	1.79	t(V-G)	-0.14	-0.89	0.02	-0.04	-1.08	-0.68

Panel C. Changes in the SMB Betas							Panel D. Changes in the HML Betas						
	Low	IVol2	IVol3	IVol4	High	L-H		Low	IVol2	IVol3	IVol4	High	L-H
Value	0.113	0.088	0.040	0.026	-0.041	0.154	Value	0.087	0.179	0.150	0.083	0.073	0.014
t-stat	2.58	1.79	0.81	0.57	-1.07	2.52	t-stat	1.38	2.93	1.96	1.20	1.14	0.18
mb2	0.038	0.038	-0.008	-0.036	-0.026	0.064	mb2	0.130	0.026	0.039	0.035	0.080	0.050
t-stat	0.73	0.80	-0.15	-0.76	-0.44	0.96	t-stat	1.65	0.40	0.76	0.56	1.11	0.51
mb3	-0.082	-0.037	-0.066	-0.094	-0.074	-0.008	mb3	-0.028	-0.123	-0.083	-0.031	0.023	-0.051
t-stat	-1.55	-0.90	-1.66	-2.05	-1.62	-0.11	t-stat	-0.41	-2.35	-1.49	-0.49	0.31	-0.48
mb4	-0.009	-0.028	0.037	0.006	-0.050	0.041	mb4	0.018	-0.042	0.090	-0.019	-0.168	0.186
t-stat	-0.17	-0.64	0.84	0.12	-1.17	0.60	t-stat	0.31	-0.66	1.72	-0.30	-2.50	2.10
Growth	0.061	-0.009	-0.075	-0.099	-0.073	0.133	Growth	0.165	0.072	0.021	-0.026	0.081	0.084
t-stat	1.36	-0.21	-1.63	-2.32	-1.50	2.04	t-stat	2.36	1.34	0.35	-0.40	1.26	0.98
V-G	0.052	0.097	0.115	0.125	0.031	-0.021	V-G	-0.079	0.107	0.129	0.109	-0.008	0.071
t(V-G)	0.91	1.54	1.70	2.15	0.53	-0.25	t(V-G)	-0.84	1.42	1.44	1.18	-0.09	0.63

Table 26. Betas at the Earnings Announcement Date

The table reports betas of the hedging portfolios that capture the value effect (Panel A) and the idiosyncratic volatility discount (Panel B). The betas measured in the three days around earnings announcement are reported alongside with the betas estimated using all returns. Idiosyncratic volatility portfolios are rebalanced each month, but tracked for three months, as described in the heading of Table 24. The daily portfolio returns around the announcement are defined as the weighted average of announcement returns to the stocks in the portfolio, and the weight is the capitalization at the end of the previous month. The market beta and the BVIX beta are estimated from the ICAPM with the BVIX, and the SMB and HML betas are estimated from the Fama-French model. The sample period is from January 1986 to December 2006.

Panel A. Value Effect

MKT	Low	IVol2	IVol3	IVol4	High	L-H
V-G ann	-0.388	-0.300	-0.279	-0.483	-0.455	-0.040
t(V-G)	<i>-6.15</i>	<i>-3.80</i>	<i>-4.99</i>	<i>-6.85</i>	<i>-5.62</i>	<i>-0.32</i>
V-G all	-0.099	0.007	-0.057	-0.162	-0.351	-0.252
t(V-G)	<i>-1.57</i>	<i>0.10</i>	<i>-0.61</i>	<i>-1.77</i>	<i>-3.55</i>	<i>-2.62</i>
Ann - All	-0.290	-0.306	-0.222	-0.321	-0.104	0.212
<hr/>						
VIX	Low	IVol2	IVol3	IVol4	High	L-H
V-G ann	-0.045	0.002	0.148	0.144	0.287	0.432
t(V-G)	<i>-0.40</i>	<i>0.02</i>	<i>1.95</i>	<i>1.63</i>	<i>3.07</i>	<i>3.35</i>
V-G all	-0.023	0.104	0.004	0.260	0.382	0.405
t(V-G)	<i>-0.26</i>	<i>0.74</i>	<i>0.03</i>	<i>2.32</i>	<i>2.75</i>	<i>3.37</i>
Ann - All	-0.023	-0.102	0.144	-0.116	-0.096	0.027
<hr/>						
SMB	Low	IVol2	IVol3	IVol4	High	L-H
V-G ann	0.669	0.469	0.334	0.366	0.156	-0.432
t(V-G)	<i>4.20</i>	<i>4.89</i>	<i>3.28</i>	<i>3.02</i>	<i>1.05</i>	<i>-2.96</i>
V-G all	0.526	0.289	0.468	0.421	0.253	-0.272
t(V-G)	<i>8.61</i>	<i>3.71</i>	<i>6.20</i>	<i>4.77</i>	<i>2.79</i>	<i>-2.74</i>
Ann - All	0.143	0.181	-0.134	-0.056	-0.098	-0.160
<hr/>						
HML	Low	IVol2	IVol3	IVol4	High	L-H
V-G ann	0.204	0.912	0.963	1.309	1.613	1.534
t(V-G)	<i>1.32</i>	<i>5.97</i>	<i>6.41</i>	<i>9.39</i>	<i>9.67</i>	<i>6.59</i>
V-G all	0.809	0.983	1.091	1.207	1.174	0.365
t(V-G)	<i>8.14</i>	<i>8.42</i>	<i>11.87</i>	<i>14.01</i>	<i>11.00</i>	<i>3.15</i>
Ann - All	-0.605	-0.071	-0.128	0.102	0.439	1.168

Panel B. IVol Discount

MKT	Value	mb2	mb3	mb4	Growth	V-G
L-H ann	-0.438	-0.393	-0.381	-0.440	-0.513	-0.040
t(L-H)	<i>-6.32</i>	<i>-5.98</i>	<i>-4.97</i>	<i>-6.91</i>	<i>-6.21</i>	<i>-0.32</i>
L-H all	-0.481	-0.565	-0.582	-0.585	-0.733	-0.252
t(L-H)	<i>-4.60</i>	<i>-4.60</i>	<i>-5.00</i>	<i>-5.05</i>	<i>-5.52</i>	<i>-2.62</i>
Ann - All	0.043	0.172	0.202	0.145	0.219	0.212

VIX	Value	mb2	mb3	mb4	Growth	V-G
L-H ann	0.087	0.055	0.077	0.162	0.442	0.432
t(L-H)	<i>1.40</i>	<i>0.69</i>	<i>0.72</i>	<i>2.08</i>	<i>3.91</i>	<i>3.35</i>
L-H all	0.199	0.245	0.172	0.374	0.604	0.405
t(L-H)	<i>1.99</i>	<i>1.19</i>	<i>1.54</i>	<i>3.39</i>	<i>3.57</i>	<i>3.37</i>
Ann - All	-0.112	-0.190	-0.095	-0.212	-0.162	0.027

SMB	Value	mb2	mb3	mb4	Growth	V-G
L-H ann	-0.552	-0.528	-0.883	-0.535	-0.992	-0.432
t(L-H)	<i>-4.91</i>	<i>-5.26</i>	<i>-7.42</i>	<i>-3.44</i>	<i>-8.28</i>	<i>-2.96</i>
L-H all	-0.808	-0.936	-0.893	-0.939	-1.080	-0.272
t(L-H)	<i>-8.11</i>	<i>-11.72</i>	<i>-7.80</i>	<i>-9.62</i>	<i>-14.67</i>	<i>-2.74</i>
Ann - All	0.255	0.408	0.010	0.404	0.088	-0.160

HML	Value	mb2	mb3	mb4	Growth	V-G
L-H ann	-0.312	0.329	0.077	0.608	1.092	1.534
t(L-H)	<i>-2.16</i>	<i>2.18</i>	<i>0.41</i>	<i>4.15</i>	<i>6.03</i>	<i>6.59</i>
L-H all	0.047	0.309	0.130	0.313	0.412	0.365
t(L-H)	<i>0.41</i>	<i>2.69</i>	<i>1.08</i>	<i>2.72</i>	<i>3.49</i>	<i>3.15</i>
Ann - All	-0.358	0.020	-0.053	0.296	0.680	1.168

Figure 1. Expected Return as a Function of Idiosyncratic Volatility and the Value of Assets in Place

The figures show the expected return, μ_V , for the firm in my model on the vertical axis. Idiosyncratic volatility, σ_I , is plotted on the left axis and the value of assets in place, B , are on the right axis. The top figure shows the expected return for the baseline values of the parameters $S = 100$, $K = 90$, $T - t = 4$, $r = 5\%$, $\sigma_S = 10\%$, $\sigma_B = 40\%$, $\sigma_\Lambda = 50\%$, $\rho_{S\Lambda} = -0.8$, $\rho_{B\Lambda} = -0.7$, $\rho_{SB} = 0.5$. The two bottom figures show the effect of setting $K = 100$ (left) or $T - t = 2$ (right).

Figure 2. Idiosyncratic Variance, (32), and the Derivative of the Expected Return with respect to Idiosyncratic Volatility and the Value of Assets in Place, (36)

The top figure plots the idiosyncratic variance, $IVar$, of the firm's return as a function of σ_I . The idiosyncratic variance is defined as the variance of the part of the firm value process that is orthogonal to the pricing kernel. σ_I measures the volatility of the idiosyncratic part in the process for the asset behind the growth options. The bottom figure plots the derivative (36) as a function of σ_I and the value of the assets in place B . Other parameters are at the baseline values $S = 100$, $K = 90$, $T - t = 4$, $r = 5\%$, $\sigma_S = 10\%$, $\sigma_B = 40\%$, $\sigma_A = 50\%$, $\rho_{SA} = -0.8$, $\rho_{BA} = -0.7$, $\rho_{SB} = 0.5$. In the top figure B is fixed at 50.

Figure 3. Risk Premium Elasticity with respect to Idiosyncratic Volatility

The top figure plots the risk premium elasticity as a function of idiosyncratic volatility, σ_I , and the value of assets in place, B . The bottom left figure plots the derivative of the elasticity with respect to idiosyncratic volatility, (37). The bottom right figure plots the second cross-derivative of the elasticity with respect to idiosyncratic volatility and the value of assets in place, (39). Other parameters are at the baseline values $S = 100$, $K = 90$, $T - t = 4$, $r = 5\%$, $\sigma_S = 10\%$, $\sigma_B = 40\%$, $\sigma_A = 50\%$, $\rho_{SA} = -0.8$, $\rho_{BA} = -0.7$, $\rho_{SB} = 0.5$.

Figure 4. Firm Value Elasticity with respect to Idiosyncratic Volatility

The top figure plots the firm value elasticity as a function of idiosyncratic volatility, σ_I , and the value of assets in place, B . The bottom left figure plots the derivative of the elasticity with respect to idiosyncratic volatility, (42). The bottom right figure plots the second cross-derivative of the elasticity with respect to idiosyncratic volatility and the value of assets in place, (44). Other parameters are at the baseline values $S = 100$, $K = 90$, $T - t = 4$, $r = 5\%$, $\sigma_S = 10\%$, $\sigma_B = 40\%$, $\sigma_\Lambda = 50\%$, $\rho_{S\Lambda} = -0.8$, $\rho_{B\Lambda} = -0.7$, $\rho_{SB} = 0.5$.