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

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Abstract

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.

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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 Barinov (2007), 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 Barinov (2007) 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 Barinov (2007) model, 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 Gompers, 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 Barinov (2007) 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 in my sample period 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 essentially 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 Barinov (2007) 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 paper proceeds as follows. In Section 2, I describe the data. In Section 3, 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 4, I look at the new issues puzzle, the relation between the BVIX factor and the investment factor. Section 4 also studies new issues puzzle in the cross-section and in the event time. In Section 5, I examine the cumulative issuance puzzle, its relation to the small growth anomaly, and its dependence on size and market-to-book. In Section 6, I conclude and discuss directions for future research.

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 100[1]. 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 3, 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

[1]For a detailed description of VIX, see Whaley (2000).

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 Barinov (2007). 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 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 [2].

In Section 4, 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)[3]. The investment-to-assets ratio is the sum of the annual changes of gross PPE (Compustat item #7) and

[2] http://mba.tuck.dartmouth.edu/pages/faculty /ken.french/

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

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 5, 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.

3 Aggregate Volatility Risk and the Small Growth Anomaly

3.1 Is the BVIX Factor Priced?

Changes in aggregate volatility provide information about future investment opportunities and future consumption. Campbell (1993) and Chen (2002) present extensions of Merton (1973) Intertemporal CAPM (henceforth ICAPM) in which aggregate volatility risk is prcied. 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) show that the most negatively correlated with changes in aggregate volatility stocks should earn a risk premium. These stocks are risky because their value drops when consumption has to be cut to increase savings.

In a recent paper, Ang, Hodrick, Xing, and Zhang (2006) use the CBOE VIX index, defined as the implied volatility of S&P 100 options, to proxy for expected aggregate volatility. They show that firms with more negative return sensitivity to the VIX index changes indeed have higher expected returns than firms with higher sensitivity. In this subsection, I test whether the BVIX factor is priced using several portfolio sets. The BVIX factor is a zero-cost portfolio long in the firms with the most negative return sensitivity to VIX increases and short in the firms with the most positive sensitivity. To start, I verify that sorting stocks on return sensitivity to the VIX index changes creates a spread in returns, which is unrelated to other priced factors. In Panel A of Table 1 I show 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 Ang, Hodrick, Xing, and Zhang (2006) document for in 1986-2000.

In Panel B, I use the Gibbons, Ross, and Shanken (1989) (hereafter - GRS) test statistics to compare the performance of the CAPM and the Fama-French model with and without the BVIX factor. The GRS statistics test 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 the more precise alpha estimates, which usually come from low volatility stocks. Because BVIX is shown to explain the alphas of high volatility firms, the GRS statistic gives quite conservative estimate of its usefulness. 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 materially improves the GRS statistic, though it still remains significant. The improvement of the alphas GRS statistic is about 17% for the 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.

Taken together, the evidence in this section implies that the BVIX factor has explanatory power beyond explaining the idiosyncratic volatility related anomalies in Barinov (2007) and is a priced factor for a broad set of portfolios.

3.2 Can the BVIX Factor Price Small Growth Firms?

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 Barinov (2007) 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 increase[4]. 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 the Barinov (2007) 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 Barinov (2007) can

[4]See, e.g., Campbell, Lettau, Malkiel, and Xu, 2001

show, for high volatility firms.

In sum, the model in Barinov (2007) 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.

Barinov (2007) 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 2, 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 2 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. Barinov (2007) finds 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 reduces 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 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.

4 The New Issues Puzzle

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 3, 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 Barinov (2007).

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 3 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 3. I conclude that using the weighting scheme proposed by Loughran and Ritter (2000) does not influence my results in a material way.

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 Barinov, 2007). 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 4, 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 in only one observation - January 2001. When I include it in the sample in the right part of Table 4, 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 Table 4 for my sample period - i.e. without January 2001, the investment factor explains 50% of the new issues puzzle, not

80%.

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 Barinov (2007). 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 5 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 5 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 5 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.

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 Barinov (2007) 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 fist 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.

5 The Cumulative Issuance Puzzle

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 3.2 and in Barinov (2007).

The missing link here is demonstrating that firms with high cumulative issuance are predominantly small and growth. This is what I show in Table 7. 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 7 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 7 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.

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 8, 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 8 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.

5.3 The Cross-Section of the Cumulative Issuance Puzzle

Similar to the analysis in the previous section, in Table 9 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 than the cumulative issuance puzzle is driven primarily by these firms.

Because of the strong relation between size and market-to-book, in Table 9 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 9 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.

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 Barinov (2007), 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 Barinov (2007) 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.

References

[1] Ang, Andrew, Robert J. Hodrick, Yuhang Xing,and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance*, v. 61, pp. 259-299

[2] Barinov, Alexander, 2007, Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns, *Working Paper*, University of Rochester

[3] Brav, Alon, Christopher Geczy, and Paul A. Gompers, 2000, Is the Abnormal Return Following Equity Issuances Anomalous?, *Journal of Financial Economics*, v. 56, 209-249

[4] Campbell, John Y., 1993, Intertemporal Asset Pricing without Consumption Data, *American Economic Review*, v. 83, pp. 487-512

[5] Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, *Journal of Finance*, v. 56, 1-43

[6] Daniel, Kent, and Sheridan Titman, 2006, Market Reactions to Tangible and Intangible Information, *Journal of Finance*, v. 61, 1605-1643

[7] Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, v. 33, 3-56

[8] Fama, Eugene F., and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics*, v. 43, pp. 153-193

[9] Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A Test of the Efficiency of a Given Portfolio, *Econometrica*, v. 57, 1121-1152

[10] Li, Erica X.L., Dmitry Livdan, and Lu Zhang, 2007, Anomalies, *Working Paper*, University of Michigan

[11] Loughran, Tim, and Jay R. Ritter, 1995, The New Issues Puzzle, *Journal of Finance*, v. 50, 23-51

[12] Loughran, Tim, and Jay R. Ritter, 1997, The Operating Performance of Firms Conducting Seasoned Equity Offerings, *Journal of Finance*, v. 52, 1823-1850

[13] Loughran, Tim, and Jay R. Ritter, 2000, Uniformly Least Powerful Tests of Market Efficiency, *Journal of Financial Economics*, v. 55, 361-389

[14] Lyandres, Evgeny, Le Sun, and Lu Zhang, 2007, The New Issues Puzzle: Testing the Investment-Based Explanation, *Review of Financial Studies*, forthcoming

[15] Merton, Robert C., 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica*, v. 41, pp. 867-887

[16] Newey, Whitney, and Kenneth West, 1987, A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, v. 55, 703-708

[17] Ritter, Jay R., 2003, Investment Banking and Security Issuance, in George Constantinides, Milton Harris, and Rene Stulz, eds.: *Handbook of Economics and Finance* (North Holland, Amsterdam)

[18] Schultz, Paul, 2003, Pseudo Market Timing and the Long-Run Underperformance of IPOs, *Journal of Finance*, v. 58, 483-517

[19] Spiess, Katherine D., and John Affleck-Graves, 1999, The Long-Run Performance of Stock Returns Following Debt Offerings, *Journal of Financial Economics*, v. 54, 45-73

[20] Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital Investments and Stock Returns, *Journal of Financial and Quantitative Analysis*, v. 39, 677-700

[21] Whaley, Robert E., 2000, The Investor Fear Gauge, *Journal of Portfolio Management*, v. 26, 12-17

[22] White, Halbert L. Jr., 1980, A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity, *Econometrica*, v. 48, 817-838

[23] Xing, Yuhang, 2007, Interpreting the Value Effect through the Q-Theory: An Empirical Investigation, *Review of Financial Studies*, forthcoming

Table 1. 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 2. 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.

Panel A. February 1986 - December 2006, January 2001 excluded

Equal-Weighted Returns

	Small	**Size2**	**Size3**	**Size4**	**Big**	**S-B**
$\boldsymbol{\alpha}_{CAPM}$	-0.864	-0.754	-0.502	-0.141	-0.071	-0.794
t-stat	*-2.03*	*-3.19*	*-2.19*	*-0.73*	*-0.61*	*-1.81*
$\boldsymbol{\alpha}_{FF}$	-0.668	-0.507	-0.176	0.123	0.123	-0.791
t-stat	*-2.58*	*-3.65*	*-1.35*	*0.95*	*1.69*	*-2.78*
$\boldsymbol{\alpha}_{ICAPM}$	-0.429	-0.422	-0.238	0.026	-0.074	-0.355
t-stat	*-0.91*	*-1.61*	*-1.05*	*0.13*	*-0.62*	*-0.71*
$\boldsymbol{\beta}_{BVIX}$	-0.461	-0.352	-0.280	-0.176	0.004	-0.465
t-stat	*-2.96*	*-3.76*	*-5.67*	*-4.02*	*0.08*	*-2.36*

Value-Weighted Returns

	Small	**Size2**	**Size3**	**Size4**	**Big**	**S-B**
$\boldsymbol{\alpha}_{CAPM}$	-1.009	-0.559	-0.397	-0.068	0.007	-1.016
t-stat	*-2.93*	*-2.52*	*-1.98*	*-0.37*	*0.05*	*-2.64*
$\boldsymbol{\alpha}_{FF}$	-0.707	-0.288	-0.028	0.236	0.237	-0.945
t-stat	*-3.90*	*-2.67*	*-0.31*	*1.83*	*2.98*	*-4.63*
$\boldsymbol{\alpha}_{ICAPM}$	-0.475	-0.175	-0.059	0.200	-0.065	-0.410
t-stat	*-1.03*	*-0.59*	*-0.24*	*0.85*	*-0.50*	*-0.83*
$\boldsymbol{\beta}_{BVIX}$	-0.566	-0.407	-0.358	-0.284	0.075	-0.642
t-stat	*-2.48*	*-2.54*	*-2.74*	*-2.76*	*2.65*	*-2.63*

Equal-Weighted Returns **Value-Weighted Returns**

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

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

Table 3. 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**
$\boldsymbol{\alpha}$	-0.702	-0.372	-0.536	-0.578	-0.326	-0.406
t-stat	*-2.27*	*-1.19*	*-2.97*	*-2.01*	*-1.08*	*-2.11*
$\boldsymbol{\beta}_{MKT}$	1.446	1.387	1.237	1.466	1.423	1.228
t-stat	*18.2*	*20.3*	*17.7*	*16.4*	*15.7*	*16.7*
$\boldsymbol{\beta}_{SMB}$			1.004			1.048
t-stat			*7.84*			7.46
$\boldsymbol{\beta}_{HML}$			-0.161			-0.211
t-stat			*-1.25*			*-1.30*
$\boldsymbol{\beta}_{BVIX}$		-0.376			-0.281	
t-stat		*-4.38*			*-1.99*	
$\Delta\boldsymbol{\alpha}/\boldsymbol{\alpha}$	47%		31%	44%		20%

Panel B. Equal-Weighted SEO Returns

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

Table 4. 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**
$\boldsymbol{\alpha}$	-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	*-1.19*	*-1.03*	*-0.01*	*-1.08*	*-0.25*	*0.58*	*-1.37*	*-0.96*	*0.27*	*-1.22*	*-0.22*	*0.71*
$\boldsymbol{\beta}_{MKT}$	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	*20.3*	*14.6*	*18.2*	*15.7*	*14.0*	*17.8*	*27.5*	*20.4*	*24.0*	*23.2*	*19.6*	*23.2*
$\boldsymbol{\beta}_{BVIX}$	-0.376		-0.374	-0.281		-0.288	-0.257		-0.255	-0.203		-0.208
t-stat	*-4.38*		*-3.58*	*-1.99*		*-1.87*	*-6.09*		*-4.64*	*-2.65*		*-2.47*
$\boldsymbol{\beta}_{INV}$		-0.589	-0.582		-0.790	-0.804		-0.515	-0.510		-0.623	-0.633
t-stat		*-2.37*	*-2.94*		*-2.33*	*-2.54*		*-3.61*	*-4.33*		*-3.51*	*-3.84*
$\Delta\boldsymbol{\alpha}/\boldsymbol{\alpha}$	47%	53%	100%	44%	85%	131%	46%	65%	110%	44%	89%	135%

Table 5. 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
$\boldsymbol{\alpha}_{none}$	0.211	-0.568	-0.970	1.181	-0.774	-0.612	0.258	1.031
t-stat	*0.78*	*-1.96*	*-2.48*	*3.68*	*-2.29*	*-1.83*	*0.92*	*2.40*
$\boldsymbol{\alpha}_{BVIX}$	0.327	-0.376	-0.533	0.860	-0.422	-0.298	0.335	0.757
t-stat	*1.26*	*-1.24*	*-1.36*	*2.61*	*-1.23*	*-0.92*	*1.15*	*1.71*
$\boldsymbol{\beta}_{BVIX}$	-0.169	-0.212	-0.490	0.321	-0.393	-0.382	-0.111	0.281
t-stat	*-3.60*	*-2.62*	*-3.80*	*3.02*	*-4.04*	*-4.44*	*-2.00*	*2.54*
$\boldsymbol{\alpha}_{INV}$	0.514	-0.250	-0.605	1.119	-0.403	-0.165	0.460	0.863
t-stat	*1.77*	*-0.90*	*-1.46*	*3.63*	*-1.15*	*-0.50*	*1.59*	*2.05*
$\boldsymbol{\beta}_{INV}$	-0.475	-0.500	-0.573	0.098	-0.581	-0.701	-0.317	0.263
t-stat	*-2.85*	*-2.46*	*-1.71*	*0.40*	*-2.16*	*-2.71*	*-1.95*	*0.92*
$\boldsymbol{\alpha}_{both}$	0.626	-0.061	-0.176	0.802	-0.058	0.143	0.535	0.593
t-stat	*2.26*	*-0.22*	*-0.48*	*2.81*	*-0.18*	*0.47*	*1.80*	*1.43*

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

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

Table 6. 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**
$\boldsymbol{\alpha}_{none}$	-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	*-1.74*	*-3.39*	*-3.40*	*-2.60*	*-1.88*	*0.64*	*-2.61*	*-4.24*	*-3.23*	*-2.44*	*-1.01*	*-0.59*
$\boldsymbol{\alpha}_{BVIX}$	-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	*-0.98*	*-2.51*	*-2.58*	*-1.64*	*-1.03*	*1.31*	*-1.03*	*-3.28*	*-2.24*	*-1.47*	*-0.12*	*0.13*
$\boldsymbol{\beta}_{BVIX}$	-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	*-1.70*	*-3.64*	*-5.35*	*-4.11*	*-4.12*	*-3.46*	*-3.06*	*-4.91*	*-3.39*	*-2.89*	*-3.92*	*-2.82*
$\boldsymbol{\alpha}_{INV}$	-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	*-0.82*	*-2.11*	*-2.09*	*-1.04*	*-0.68*	*1.42*	*-1.23*	*-3.04*	*-1.20*	*-0.30*	*0.49*	*-0.03*
$\boldsymbol{\beta}_{INV}$	-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	*-1.28*	*-2.51*	*-3.27*	*-3.27*	*-2.28*	*-1.89*	*-2.08*	*-3.28*	*-5.29*	*-4.76*	*-3.38*	*-1.31*
$\boldsymbol{\alpha}_{both}$	-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	*-0.17*	*-1.29*	*-1.27*	*-0.23*	*0.05*	*2.03*	*0.13*	*-1.89*	*-0.23*	*0.63*	*1.38*	*0.70*

Table 7. 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	*6.08*	*4.10*	*3.74*	*3.60*	*3.23*	*-3.95*
MB	2.501	2.114	2.976	4.196	5.425	2.924
t-stat	*11.24*	*15.60*	*4.63*	*7.42*	*21.62*	*9.98*

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	*5.4*	*3.8*	*5.3*	*3.8*	*0.1*	*3.1*
MB2	0.194	0.162	0.122	0.084	0.043	0.151
t-stat	*7.2*	*5.9*	*4.3*	*3.5*	*1.0*	*4.2*
MB3	0.309	0.262	0.170	0.124	0.031	0.278
t-stat	*8.0*	*9.4*	*9.0*	*5.8*	*1.1*	*12.1*
MB4	0.450	0.445	0.316	0.210	0.049	0.401
t-stat	*9.8*	*9.5*	*8.3*	*8.0*	*1.9*	*12.9*
High	0.662	0.721	0.563	0.354	0.074	0.588
t-stat	*16.8*	*18.8*	*11.8*	*14.7*	*2.9*	*23.0*
H-L	0.558	0.642	0.452	0.285	0.068	0.489
t(H-L)	*17.7*	*20.0*	*12.5*	*15.7*	*1.8*	*9.4*

Table 8. 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**
$\boldsymbol{\alpha}$	-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	*-1.43*	*-2.25*	*-0.85*	*-1.31*	*-1.38*	*-0.29*	*-3.04*	*-2.20*	*-1.32*	*-3.00*	*-1.91*	*-1.05*
$\boldsymbol{\beta}_{MKT}$	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	*7.26*	*4.52*	*5.38*	*6.11*	*4.29*	*5.12*	*8.98*	*5.74*	*6.99*	*7.98*	*5.72*	*6.89*
$\boldsymbol{\beta}_{BVIX}$	-0.339		-0.338	-0.273		-0.277	-0.131		-0.129	-0.106		-0.110
t-stat	*-3.45*		*-3.11*	*-2.09*		*-1.99*	*-2.10*		*-1.69*	*-1.48*		*-1.34*
$\boldsymbol{\beta}_{INV}$		-0.331	-0.324		-0.470	-0.483		-0.492	-0.490		-0.533	-0.538
t-stat		*-1.45*	*-1.81*		*-1.68*	*-1.92*		*-4.33*	*-5.10*		*-4.19*	*-4.69*
$\Delta\boldsymbol{\alpha}/\boldsymbol{\alpha}$	43%	29%	72%	41%	46%	88%	18%	51%	69%	16%	57%	74%

Table 9. 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**
$\boldsymbol{\alpha}_{none}$	0.035	-0.408	-1.148	1.183	-0.490	-0.970	-0.540	-0.050
t-stat	*0.15*	*-1.70*	*-2.71*	*4.29*	*-1.43*	*-3.61*	*-2.97*	*-0.19*
$\boldsymbol{\alpha}_{BVIX}$	0.200	-0.152	-0.493	0.693	-0.169	-0.638	-0.299	-0.130
t-stat	*0.83*	*-0.56*	*-0.93*	*1.79*	*-0.45*	*-2.09*	*-1.52*	*-0.47*
$\boldsymbol{\beta}_{BVIX}$	-0.183	-0.280	-0.699	0.517	-0.361	-0.355	-0.254	0.107
t-stat	*-3.74*	*-3.54*	*-3.05*	*2.61*	*-3.12*	*-3.81*	*-4.79*	*1.30*
$\boldsymbol{\alpha}_{INV}$	0.181	-0.209	-1.005	1.186	-0.478	-0.783	-0.204	0.274
t-stat	*0.74*	*-1.01*	*-2.64*	*4.28*	*-1.40*	*-3.44*	*-1.31*	*0.99*
$\boldsymbol{\beta}_{INV}$	-0.230	-0.312	-0.224	-0.006	-0.018	-0.293	-0.527	-0.509
t-stat	*-1.45*	*-1.47*	*-0.52*	*-0.02*	*-0.06*	*-1.28*	*-3.18*	*-3.37*
$\boldsymbol{\alpha}_{both}$	0.343	0.043	-0.359	0.702	-0.162	-0.456	0.032	0.194
t-stat	*1.38*	*0.19*	*-0.84*	*2.22*	*-0.46*	*-1.80*	*0.18*	*0.70*