Institutional Ownership and Aggregate Volatility Risk

Alexander Barinov

Terry College of Business
University of Georgia

E-mail: **abarinov@terry.uga.edu**
http://abarinov.myweb.uga.edu/

This version: November 2009

Abstract

The paper shows that the difference in aggregate volatility risk can explain why several anomalies are stronger among the stocks with low institutional ownership (IO). Because of their desire to hedge against aggregate volatility or to exploit their competitive advantage in obtaining and processing information, coupled with the dislike of uncertainty and volatility, institutions tend to stay away from the stocks with extremely low and extremely high levels of firm-specific uncertainty and growth options. Consequentially, the spread in the measures of uncertainty and growth options is wider for low IO stocks, and the same is true about the differential in aggregate volatility risk. I demonstrate empirically that the ICAPM with the aggregate volatility risk factor can completely explain why the negative relation between market-to-book, idiosyncratic volatility, turnover, and analyst disagreement, on the one hand, and future returns on the other is stronger for the stocks with low IO. The same mechanism explains why the positive relation between IO and future returns is stronger for growth firms and high uncertainty firms.

JEL Classification: G12, G14, G23, E44, D80
Keywords: Aggregate volatility risk, institutional ownership, value effect, idiosyncratic volatility discount, turnover effect, analyst disagreement effect, anomalies

1 Introduction

Institutional ownership (henceforth IO) is long recognized to be driven by a long list of firm characteristics[1], many of which can proxy for systematic risk. However, the existing asset pricing studies usually use IO as a proxy for either investor sophistication[2] or short sale constraints[3]. Therefore, the link between IO and numerous anomalies is usually interpreted as the evidence that these anomalies stem from investors' data-processing biases and persist because of limits to arbitrage.

This paper presents a risk-based story that explains why several important anomalies - the value effect (Fama and French, 1993), the idiosyncratic volatility discount (Ang, Hodrick, Xing, and Zhang, 2006), the turnover effect (Datar, Naik, and Radcliffe, 1998), and the analyst disagreement effect (Diether, Malloy, and Scherbina, 2002) - are stronger for low IO firms. The explanation is aggregate volatility risk: in the subsample with low IO, the arbitrage portfolios that exploit the aforementioned anomalies severely underperform the CAPM when expected aggregate volatility increases.

The reason why the sorts on market-to-book, idiosyncratic volatility, turnover, or analyst disagreement produce wider aggregate volatility risk differential in the low IO subsample is that, as I document in this paper, institutions tend to stay away from the firms with extreme levels of volatility/uncertainty and growth options. On the one hand, portfolio managers dislike the stocks with high volatility/uncertainty (see Shleifer and Vishny, 1997), which makes them decide against owning stocks with high market-to-book, high idiosyncratic volatility, high analyst disagreement, or high turnover. On the other hand, portfolio managers like the protection against aggregate volatility risk offered by the stocks with high levels of volatility and growth options[4]. Portfolio managers also recognize that they need some level of uncertainty to use their comparative advantage in access to information and in ability to process it. As a result, institutions ignore both the firms with low uncertainty (considering them unattractive) and the firms with high uncertainty (con-

[1]See, for example, Falkenstein (1996), Del Guercio (1996), Gompers and Metrick (2001)

[2]Bartov, Radhakrishnan, and Krinsky (2000), Collins, Gong, and Hribar (2003)

[3]Nagel (2005), Asquith, Pathak, and Ritter (2005)

[4]See Barinov (2009a) for the evidence that growth firms and high idiosyncratic volatility firm load negatively on the aggregate volatility risk factor, and Barinov (2009b) and Barinov (2009c) for similar evidence on high turnover firms and firm with high analyst forecast dispersion.

sidering them too dangerous). Sorting on uncertainty measures in the low IO subsample therefore produces the widest spreads in uncertainty.

Barinov (2009a) shows that higher idiosyncratic volatility and abundant growth options mean lower aggregate volatility risk. First, idiosyncratic volatility increases when aggregate volatility goes up (see Campbell et al., 2001, for empirical evidence). Higher idiosyncratic volatility during periods of high aggregate volatility means that the value of growth options becomes less sensitive to the value of the underlying asset (because the delta of the option declines in volatility) and the growth options become therefore less risky precisely when risks are high. This effect is stronger for the firms with higher idiosyncratic volatility. Hence, firms with high idiosyncratic volatility and valuable growth options will have procyclical market betas and will suffer smaller losses when aggregate volatility increases and the risk and expected returns of all firms go up.

Second, all else equal, growth options increase in value when idiosyncratic volatility of the underlying asset increases (see Grullon, Lyandres, and Zhdanov, 2007, for empirical evidence). That makes the reaction of growth options to the increases of aggregate volatility (usually coupled with increases in idiosyncratic volatility) less negative. This effect is also stronger for high idiosyncratic volatility firms, therefore high idiosyncratic volatility firms, especially if they possess valuable growth options, tend to lose less value than other firms with similar market betas when aggregate volatility and idiosyncratic volatility both increase.

The fact that both the stocks with the lowest and the highest idiosyncratic volatility and market-to-book end up in the low IO subsample means that the sorts on idiosyncratic volatility (market-to-book) in this subsample will create the largest spread in idiosyncratic volatility (market-to-book) and, consequentially, the largest spread in exposure to aggregate volatility risk. Hence, the stronger idiosyncratic volatility discount and the stronger value effect for the lowest IO firms should be explained by aggregate volatility risk. The same should be true about the turnover effect and the analyst disagreement effect, because both turnover and analyst forecast dispersion are strongly correlated with idiosyncratic volatility.

Aggregate volatility risk is the risk of losing value when expected aggregate volatility unexpectedly increases. Campbell (1993) creates a model where increasing aggregate volatility is synonymous with decreasing expected future consumption. Investors would require a lower risk premium from the stocks the value of which correlates positively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing and precautionary savings motives. Chen (2002) adds in the precautionary savings motive and concludes that the positive correlation of asset returns with aggregate volatility changes is desirable, because such assets deliver additional consumption when investors have to consume less in order to boost precautionary savings. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the notion of aggregate volatility risk. They show that the stocks with the most positive sensitivity to aggregate volatility increases have abnormally low expected returns and that the portfolio tracking expected aggregate volatility earns a significant risk premium. This paper builds on this literature and shows that aggregate volatility risk helps to explain the link between IO and several asset pricing anomalies.

I start my empirical tests by demonstrating that institutional investors indeed tend to ignore the stocks with the extreme levels of market-to-book, idiosyncratic volatility, turnover, and analyst disagreement. In cross-sectional regressions, the sign of the relation between IO and these variables is positive when their values are low and becomes negative when their values become higher. I confirm this result using double sorts on market-to-book and IO and double sorts on idiosyncratic volatility and IO, which demonstrate that in the market-to-book (idiosyncratic volatility) sorts the spread in market-to-book (idiosyncratic volatility) is significantly larger if this sort is performed in the lower IO group. The same is true about aggregate volatility risk: buying value and shorting growth, as well as buying low and shorting high idiosyncratic volatility firms means greater exposure to aggregate volatility risk if one follows these strategies in the lower IO subsample.

I proceed with demonstrating that the difference in aggregate volatility risk is enough to explain why the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect are stronger for the firms with low IO. When I look at the CAPM alphas, the difference in the magnitude of these four effects between the lowest and the highest IO quintiles varies between 0.5% and 1% per month. However, in the two-factor ICAPM with the market factor and the aggregate volatility risk factor this difference is reduced by more than a half and usually becomes insignificant.

Next, I turn to explaining the positive link between IO and future returns. Gompers and Metrick (2001) is one of the first studies to document this link. They interpret the ability of IO to predict future returns either to the ability of the portfolio managers to pick the right stocks, or to the demand pressure institutions exert on prices. Yan and Zhang (2008) and Jiao and Liu (2008) show that the effect of IO on prices is higher for small stocks, growth stocks, and high uncertainty stocks, consistent with the argument in Gompers and Metrick (2001).

The evidence in Yan and Zhang (2008) and Jiao and Liu (2008) can be potentially explained by aggregate volatility risk. As I show in this paper, in the subsamples with high (low) uncertainty institutions tend to pick the firms with lower (higher) uncertainty and therefore with higher (lower) aggregate volatility risk. Hence, my story also predicts that the relation between IO and future returns should be the most positive for high uncertainty firms.

Since the relation between IO and aggregate volatility risk should have different sign for high and low uncertainty firms, it is an empirical question what is the correlation between IO and aggregate volatility risk on average for all firms. The results of cross-sectional regressions suggest that, holding all else equal and not controlling for the concavity of the relation between IO and uncertainty, on average lower uncertainty means higher IO, and consequentially, higher IO implies higher aggregate volatility risk.

In the asset pricing tests I find that the two-factor ICAPM with the market factor and the aggregate volatility risk factor can explain the positive relation between IO and future returns, as well as why this relation is stronger if market-to-book or volatility/uncertainty measures are high.

I also perform two important robustness checks for all results discussed above. First, I replace my aggregate volatility factor by the change in expected aggregate volatility (as proxied for by the change in the VIX index), which is the variable mimicked by the aggregate volatility factor. Using the change in VIX I show that during increases in expected aggregate volatility the arbitrage portfolios exploiting the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect indeed underperform the CAPM more severely, if these arbitrage portfolios are formed in the low IO subsample. I also demonstrate that, on average, low (high) IO firms tend to beat (trail) the CAPM when expected aggregate volatility increases, and this is especially true in the subsamples of growth firms and firms with high volatility/uncertainty.

Second, I turn to the conditional CAPM as a more conventional way to measure risk and its changes. Barinov (2009a) argues that one reason why growth firms and volatile firms have low expected returns is because they become less risky in recessions. In recessions, both aggregate volatility and idiosyncratic volatility increase, which means that the value of growth options becomes less sensitive to the value of the underlying asset and the growth options therefore become less risky precisely when risks are high. This effect is stronger for volatile firms. Hence, volatile firms and growth firms should have procyclical market betas. Barinov (2009a) confirms this prediction empirically using the conditional CAPM.

If sorting on volatility/uncertainty measures and market-to-book creates larger spreads in the sorting variables within the low IO subsample, I expect that the arbitrage portfolios exploiting the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect will have more countercyclical market betas in the low IO subsample. I estimate the conditional CAPM and show that this prediction is strongly supported by the data. Similarly, consistent with aggregate volatility risk being the explanation of the positive relation between IO and future returns, low (high) IO firms have procyclical (countercyclical) market betas, and this is especially true in the growth subsample and the high uncertainty subsample. However, consistent with the Lewellen and Nagel (2006) critique, the change in the betas of the arbitrage portfolios, while goes in the right direction, is too small to explain the anomalies in question, which points towards the ICAPM as the right model to explain the anomalies.

The paper proceeds as follows. Section 2 describes the data sources. Section 3 shows that institutional investors tend to avoid the firms with extreme levels of market-to-book and volatility, and demonstrates the consequent pattern in aggregate volatility risk exposure in double sorts on market-to-book/volatility and IO. Section 4 explains the relation between the anomalies and IO using the aggregate volatility risk factor. Section 5 uses aggregate volatility risk factor to explain both the positive relation between IO and future returns and why this relation is stronger for growth firms and high volatility/uncertainty firms. Section 6 performs the robustness checks, first, replacing the aggregate volatility risk factor by the change in expected aggregate volatility and, second, estimating conditional CAPM instead of the ICAPM. Section 7 concludes.

2 Data

2.1 Data Sources

The data in the paper come from CRSP, Compustat, IBES, Thompson Financial, and the CBOE indexes databases. The sample period is from January 1986 to December 2006. IO is the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. If the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero IO. If the stock's capitalization is below the 20th NYSE/AMEX percentile, its IO is assumed to be missing. The results in the paper are robust to including in the sample the stocks from the bottom size quintile.

Following Nagel (2005), in asset pricing tests I use residual IO to eliminate the tight link between size and IO and to make sure that I am not capturing any size effects. Residual IO is the residual from

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

fitted to all firms within each separate quarter.

In Section 4, I look at four anomalies: the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect. I measure the value effect as the return differential between the bottom and top market-to-book quintiles. Market-to-book is market value of equity (Compustat item #25 times Compustat item #199) over the sum of book equity (Compustat item #60) and deferred taxes (Compustat item #74). The quintiles are rebalanced annually, and the market-to-book is always from the fiscal year ending no later than in June of the sorting year.

I define the idiosyncratic volatility discount as the return differential between the lowest and the highest idiosyncratic volatility quintile. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each month (at least 15 valid observations are required). The idiosyncratic volatility quintiles are formed using the previous month idiosyncratic volatility and are rebalanced monthly.

The turnover effect is the difference in returns between the firms with low turnover and high turnover. Turnover is measured monthly and averaged in each firm-year (at least 5 months with valid observations are required). NASDAQ (exchcd=3) turnover is divided by 2 to eliminate double-counting. The turnover quintiles are rebalanced annually.

The analyst disagreement effect is the return differential between the lowest and highest analyst disagreement quintile. Analyst disagreement is measured as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). Analyst disagreement is set to missing for the firms with stock price lower than $5. The data on analyst forecasts are from IBES.

My proxy for expected aggregate volatility is the old VIX index. It is calculated by CBOE and measures the implied volatility of one-month put and call options on S&P 100. 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. The availability of the VIX index determines my sample period that starts from January 1986 and ends in December 2006.

To estimate the conditional CAPM in Section 6, I employ four commonly used conditioning variables: the dividend yield, the default premium, the risk-free rate, and the term premium. I define the dividend yield, (DIV_t), as the sum of dividend payments to all CRSP stocks over the previous 12 months, divided by the current value of the CRSP value-weighted index. The default spread, (DEF_t), is the yield spread between Moody's Baa and Aaa corporate bonds. The risk-free rate is the one-month Treasury bill rate, (TB_t). The term spread, ($TERM_t$), is the yield spread between ten-year and one-year Treasury bond. The data on the dividend yield and the risk-free rate are from CRSP. The data on the default spread and the term spread are from FRED database at the Federal Reserve Bank at St. Louis.

2.2 Aggregate Volatility Risk Factor

I define FVIX, my aggregate volatility risk factor, as a factor-mimicking portfolio that tracks the daily changes in the VIX index. The ICAPM suggests that the right variable to mimic is the innovation to the state variable (expected aggregate volatility). As Ang, Hodrick, Xing, and Zhang (2006) show, VIX index is close to random walk at the daily level, therefore its daily change is a suitable proxy for the innovation in expected aggregate volatility.

I regress the daily changes in VIX on the daily excess returns to the six size and book-to-market portfolios (sorted in two groups on size and three groups on book-to-market). The fitted part of this regression less the constant is the FVIX factor. I cumulate returns to the monthly level to get the monthly return to FVIX. All results in the paper are robust to changing the base assets from the six size and book-to-market portfolio to the ten industry portfolios (Fama and French, 1997) or the five portfolios sorted on past sensitivity to VIX changes (Ang, Hodrick, Xing, and Zhang, 2006). The daily returns to the six size and book-to-market portfolios and the ten industry portfolios come from Kenneth French website.

By construction, FVIX has a positive correlation (0.53, t-statistic 9.82) with the innovation to expected aggregate volatility. Thus, a negative FVIX beta means negative reaction to unexpected increases in expected aggregate volatility, i.e., aggregate volatility risk.

In my sample period, FVIX loses about 1% per month, t-statistic -4.35. This low return is not surprising, because FVIX is the best possible hedge against aggregate volatility risk. Also, FVIX is strongly negatively correlated with the market factor (the correlation is -0.79, t-statistic -20.7), because market volatility usually increases when market drops. The market beta of the FVIX factor is -0.68, t-statistic -11.5. The CAPM alpha of the FVIX factor is -56 bp per month, t-statistic -3.0, suggesting that FVIX has a good potential to complement the market factor in the ICAPM.

Prior research shows that FVIX is useful in explaining several prominent anomalies: Barinov (2009a) shows that FVIX can explain the value effect and the idiosyncratic volatility discount (the negative cross-sectional relation between idiosyncratic volatility and future returns). Barinov (2009b) demonstrates that FVIX can explain the negative cross-sectional relation between turnover and future returns (the turnover effect), and Barinov (2009c) shows that FVIX explains the analyst disagreement effect (lower future returns to firms with higher dispersion of analyst forecasts).

3 IO and Firm Characteristics

3.1 Idiosyncratic Volatility and Growth Options

In this subsection, I establish the concave relation between IO and the variables related to idiosyncratic volatility and growth options by using Fama-MacBeth (1973) cross-sectional regressions. Aside from these variables, I use the standard controls used by Gompers and Metrick (2001) and related papers: size, age, the dummy variable for membership in the S&P 500 index, the level of stock price, the cumulative returns in the past three months and in the past year without the most recent quarter, and the dividend yield. All firm characteristics are measured in the quarter before the one for which IO is reported.

The SEC regulation requires to report the holdings of securities that exceed $200,000. For microcaps, many institutions are likely to own a smaller amount of shares, because they do not intend to become a blockholder and fear that a larger amount would be difficult to trade if needed. Thus, for microcaps a significant fraction of IO may go unreported in 13Fs. I decide therefore to discard from my sample the firms with market cap below the 20th NYSE/AMEX percentile, as Nagel (2005) also did. However, unreported robustness checks show that keeping these observations in the sample does not materially impact my results.

The hypothesis I am testing is that institutions are staying away from the firms with both extremely low and extremely high levels of volatility. The reasons why institutions dislike high idiosyncratic volatility are described, for example, in Shleifer and Vishny (1997). First, while the investors can presumably diversify away the idiosyncratic risk, the portfolio manager is underdiversified and will avoid idiosyncratic volatility if the interests of the manager and the investors are not perfectly aligned. Second, greater idiosyncratic volatility means a higher chance of getting a margin call and having to close the correct bet if the prices swerve in the opposite direction.

On the other hand, institutional investors also have reasons to avoid stocks with low levels of idiosyncratic volatility. First, they arguably have comparative advantage in gathering and processing information, and therefore need some uncertainty about the stock value in order to make use of this comparative advantage. Second, as Barinov (2009a) shows, low idiosyncratic volatility firms underperform the CAPM during increases in expected aggregate volatility, which in undesirable both for investors and the portfolio managers.

Similar argument can be made about other related variables, such as turnover, analyst forecast dispersion, and market-to-book, which are strongly correlated with idiosyncratic volatility. I predict that in the regression of IO on all these variables and their squares the variables will have positive coefficients, and their squares will have negative coefficients. Moreover, both coefficients will be such that IO peaks for the level of idiosyncratic volatility (turnover, market-to-book, analyst disagreement) between the minimum and the maximum sample values of these variables. In other words, the regressions of IO on idiosyncratic volatility and idiosyncratic volatility squared should show that IO increases with idiosyncratic volatility when idiosyncratic volatility is low, then peaks at some intermediate value of idiosyncratic volatility, and begins to decrease with idiosyncratic volatility as idiosyncratic volatility becomes high. The same should be true if one replaces idiosyncratic volatility with turnover, market-to-book, or analyst forecast dispersion.

In Panel A of Table 1 I regress IO (in percentage) on the controls and one of the four variables of interest plus its square. All variables are transformed into percentage ranks to eliminate their huge positive skewness. Therefore, the significant coefficient of -0.09 on idiosyncratic volatility in the bottom left panel means that as idiosyncratic volatility increases from the 25th to the 75th percentile, IO will decrease by $-0.09 \cdot (-50) = 4.5\%$.

However, the next column of the bottom left shows that the link between idiosyncratic volatility is more complicated, because, consistent with my hypothesis, after adding the squared volatility the coefficient on idiosyncratic volatility becomes significantly positive, and the coefficient on its square comes out significantly negative. This is consistent with similar evidence reported in Falkenstein (1996).

The values of the coefficients suggest that IO peaks at $0.367/(2 \cdot 0.0048) = 38$th idiosyncratic volatility percentile. At the 10th volatility percentile, IO reacts by a $0.367 - 2 \cdot 0.0048 \cdot 10 = 0.27\%$ increase to the increase of idiosyncratic volatility by one percentile. At the 90th volatility percentile, IO reacts by a $0.367 - 2 \cdot 0.0048 \cdot 90 = -0.5\%$ decrease to the increase of idiosyncratic volatility by one percentile.

The results with idiosyncratic volatility replaced by analyst forecast dispersion (bottom right panel) are very similar. In the regressions with market-to-book I observe that IO peaks at the 15th market-to-book quintile, suggesting that institutions almost always prefer lower market-to-book levels, unless these levels are below the 15th percentile. In the regressions with turnover, the peak is at the 97th turnover quintile, meaning that institutions almost always prefer higher turnover to lower. This probably not surprising, because high turnover can mean both high liquidity and high disagreement, and institutions always prefer higher liquidity. While the relation between the disagreement part of turnover and IO may peak at intermediate values of turnover, the presence of the liquidity part will create the impression that turnover is almost always positively related with IO.

In Panel B of Table 1 I try putting several volatility measures and market-to-book in one regression to control for the correlations between them. I find that the coefficients do not change much compared to Panel A. I still find that in the regressions with the squared variables all variables have significantly positive coefficients and all squares have significantly negative coefficients. The only two exceptions are market-to-book, which changes its sign in the presence of analyst forecast dispersion and its square, and the squared analyst forecast dispersion, which becomes positive and insignificant in the presence of squared turnover.

To sum up, in this subsection I find that IO significantly increases in idiosyncratic volatility, market-to-book, turnover, and analyst disagreement if these variables are low, and significantly decreases in them if these variables are high. This implies that institutions prefer firms with intermediate values of idiosyncratic volatility, market-to-book, turnover, and analyst disagreement, and the low IO subsample will include the firms with both extremely high and extremely low levels of the four variables. Thus, sorting on any of these variables in the low IO subsample will create a wider spread in the values of this variable and, since all these variables are related to aggregate volatility risk (see Barinov, 2009a, 2009b, 2009c), a wider spread in aggregate volatility risk. The wider spread in aggregate volatility risk makes it unsurprising that the value effect, the turnover effect, the idiosyncratic volatility discount, and the analyst disagreement effect are all stronger in the low IO subsample.

3.2 Aggregate Volatility Risk

In Table 2, I perform double sorts on IO and market-to-book, as well as on IO and idiosyncratic volatility, to demonstrate more visibly how the correlation between IO and market-to-book (idiosyncratic volatility) changes its sign when market-to-book (idiosyncratic volatility) increases, and how this pattern is transformed into a similar pattern in exposure to aggregate volatility risk.

In the left part of Panel A I sort firms independently into five quintiles on IO and idiosyncratic volatility and report the median values of market-to-book for each portfolio (the medians are computed separately for each portfolio and each quarter and then averaged across quarters). I find that in the lowest market-to-book quintile, firms with the lowest level of IO have the median market-to-book that is by 8% lower than that of the firms with the highest level of IO. However, in the highest market-to-book quintile, firms with the lowest level of IO beat the firms with the highest level of IO by 19% in terms of median market-to-book. As a result, the market-to-book differential between value and growth firms is by 25% higher in the lowest IO quintile. All these differences are highly statistically significant.

In the right part of Panel A, I look at the FVIX betas in the same five-by-five sorts on IO and market-to-book. FVIX is my aggregate volatility factor that mimics daily changes in the VIX index, the implied volatility of S&P 100 options. The daily returns to the factor-mimicking portfolios are then cumulated to the monthly level. The FVIX betas in Table 2 are from the Fama-French model augmented with FVIX (i.e., the monthly excess returns to each of the 25 portfolios are regressed on the excess market return, SMB, HML, and FVIX, and the slope on FVIX is reported). The results from the two-factor ICAPM with the market factor and FVIX are similar.

The right part of Panel A documents two results. Firstly and most importantly, the difference in FVIX betas between growth and value firms is 0.105, t-statistic 0.35, in the highest IO quintile and 1.881, t-statistic 4.69, in the lowest IO quintile. This is consistent with my prediction that the spread in market-to-book and aggregate volatility risk increases from the highest to the lowest IO quintile, but the difference may seem somewhat extreme. Indeed, sorting on market-to-book produces a large spread in market-to-book even in the highest IO quintile. As unreported results suggest, the answer is the use of the augmented Fama-French model. By construction, the HML factor captures the majority of the risk differential between value and growth, and the FVIX factor in the augmented Fama-French model picks up what is left. In the ICAPM with the market factor and FVIX (results not reported to save space) the FVIX beta differential between value and growth is large and significant both in the highest and the lowest IO quintiles, but the FVIX beta differential is still several times wider in the lowest IO quintile.

Second, I observe that while the FVIX beta differential between low and high IO firms increases monotonically from value to growth subsample (consistent with my prediction), it remains positive even in the bottom market-to-book quintile. If FVIX betas in the five-by-five sorts are driven by market-to-book, I would expect the FVIX beta differential between low and high IO firms to be negative in the value quintile, because in these quintile high institutional firms have higher market-to-book (see the left part of Panel A). Looking at the FVIX betas from the ICAPM does not change the results. I conclude therefore that the FVIX factor has the potential to explain why IO is positively related to future return and why this relation is stronger for growth firms.

In Panel B, I look at the five-by-five independent sorts on idiosyncratic volatility and IO. The results are even stronger than in Panel A. In the lowest volatility quintile, the median idiosyncratic volatility of the firms with high IO is by 18% larger than the median volatility of low IO firms. In the highest volatility quintile, the difference is the opposite: firms with the lowest level of IO beat the firms with the highest level of IO in terms of idiosyncratic volatility by 28%. Moreover, the differential in median idiosyncratic volatility between the highest and the lowest volatility quintiles is by whole 65% wider in the lowest IO quintile than in the highest IO quintile. All differences are statistically significant.

In the right part of Panel B I look at the FVIX betas from the Fama-French model with FVIX. I observe that the FVIX beta differential between the highest and the lowest volatility quintile increases from 0.955, t-statistic 2.69, in the highest IO quintiles, to 2.153, t-statistic 6.92, in the lowest IO quintile, t-statistic for the difference 2.61. The difference in the FVIX betas of the high minus low volatility portfolio is comparable to the corresponding difference in the median idiosyncratic volatility (see the left part of Panel B). I conclude that the loadings on FVIX can potentially explain why the idiosyncratic volatility discount is stronger for low IO firms.

Also, the FVIX beta differential between high and low IO quintiles is quite weak (though still positive) in the low volatility quintiles, but it becomes significantly more positive in the high volatility quintiles (consistent with my story). I conclude that the FVIX factor is a potential explanation why the positive relation between IO and future returns is stronger for high volatility firms.

In results not reported for brevity, I also look at the double sorts on IO and either turnover or analyst disagreement and obtain the same results in terms of the differentials in the FVIX betas and the median firm characteristics.

To sum up, Table 2 shows the change in the sign of the correlation between IO and market-to-book (idiosyncratic volatility) as market-to-book (idiosyncratic volatility) increases. The consequent wider differential in market-to-book (idiosyncratic volatility) when the firms are sorted on market-to-book (idiosyncratic volatility) in the lower IO quintile corresponds to a similar wider differential in FVIX betas, which suggests that aggregate volatility risk can potentially explain why the value effect (the idiosyncratic volatility discount) is stronger in the low IO subsample. The same is true about the turnover effect and the analyst disagreement effect.

4 IO, Anomalies, and Aggregate Volatility Risk

In this subsection, I use the aggregate volatility risk factor (FVIX) to explain why four prominent anomalies - the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect - are stronger for the firms with low IO. Prior research (Barinov, 2009a, 2009b, 2009c) shows that idiosyncratic volatility, market-to-book, turnover, and analyst disagreement are all negatively correlated with aggregate volatility risk, and this correlation explains their cross-sectional correlation with future returns (i.e., the anomalies in question). The story in this paper is that the anomalies are stronger in the low IO subsample, because institutions tend to avoid the firms with extremely low and extremely high levels of idiosyncratic volatility, market-to-book, turnover, or analyst disagreement. Hence, these firms end up in the low IO group, and sorting on either of the four variables in the low IO subsample creates a wider differential in the values of the sorting variable and, as a consequence, in aggregate volatility risk.

4.1 Value Effect

In Panel A of Table 3, I start with looking at the value effect, defined as the difference in returns between the lowest and the highest market-to-book quintiles, in each IO quintile. In the top two rows I confirm the result in Nagel (2005), who finds that the CAPM and Fama-French (1993) alphas of the value minus growth arbitrage portfolio are significantly larger in the lowest institutional quintile.

In the next pair of rows, I report the ICAPM alphas and the FVIX betas from the ICAPM. First, I find that adding the FVIX factor uniformly reduces the value effect in all IO quintiles by about two thirds compared to the CAPM alphas and makes it at most marginally significant. This evidence is consistent with Barinov (2009a), who also finds that aggregate volatility risk can almost completely explain the value effect.

Second, I find that while the CAPM alphas of the value minus growth portfolios in the lowest and the highest IO quintile are different by 58 bp per month, t-statistic 2.27, the similar difference in the ICAPM alphas is only 24 bp per month, t-statistic 0.96. This is consistent with my hypothesis that aggregate volatility risk, not short-sale constraints or investor sophistication, is the explanation of why the value effect is stronger for low IO firms.

Third, I show that the FVIX beta of the value minus growth portfolio increases in absolute magnitude from -1.09, t-statistic -8.09, in the highest IO quintile to -1.69, t-statistic -6.67, in the lowest IO quintile, the difference being significant with t-statistic -2.29. Since FVIX is positively correlated with VIX changes by construction, the difference in the FVIX betas shows that the value minus growth portfolio underperforms the CAPM during increases in expected aggregate volatility by a greater amount if formed in the lowest IO quintile. It means that the exposure of the value minus growth portfolio to aggregate volatility risk increases in IO, just as my story predicts.

In the last two rows of Panel A, I look at the alphas and the FVIX betas of the value minus growth portfolio estimated from the Fama-French model augmented with FVIX. The alphas of the Fama-French model with FVIX improve by at most 20 bp per month compared to the Fama-French model itself, which is not surprising, because the Fama-French model includes the HML factor and, in a sense, explains the value effect by the value effect. However, after I control for the FVIX factor, the difference in the alphas of the value minus growth portfolio between the lowest and the highest IO quintile declines from 54 bp per month, t-statistic 2.37, to 36 bp per month, t-statistic 1.59. The difference in the FVIX betas of the value minus growth portfolio between the lowest and the highest IO quintile is -1.382, t-statistic -2.31, meaning that the exposure of the value minus growth strategy to aggregate volatility risk decreases with IO, and, according to the alphas, this difference in aggregate volatility risk is enough to explain why the value effect also decreases with IO.

4.2 Idiosyncratic Volatility Discount

In Panel B of Table 3, I look at the variation in the idiosyncratic volatility discount across IO quintiles. I define the idiosyncratic volatility discount as the return to the arbitrage portfolio long in the lowest idiosyncratic volatility quintile and short in the highest idiosyncratic volatility quintile (henceforth, the low minus high volatility portfolio). In the top two rows I confirm the finding of Nagel (2005) that the CAPM and the Fama-French alphas of the low minus high volatility portfolio are significantly larger in the lowest IO quintile.

In the next pair of rows, I report the ICAPM alphas and FVIX betas of the low minus high volatility portfolio for each IO quintile. I find that controlling for FVIX diminishes the differential in the alphas of the low minus high volatility portfolio between the lowest and the highest IO quintile from 1.23% per month, t-statistic 4.27, to 0.68%, t-statistic 3.6.

The reduction in the alphas is driven by a large differential in the FVIX betas of the low minus high volatility portfolio: in the lowest (highest) IO quintile the FVIX beta is -1.943, t-statistic -14.8 (-0.973, t-statistic -10.2), the difference being highly significant with t-statistic -8.59. The difference in the FVIX betas demonstrates that, consistent with my story, during increases in expected aggregate volatility, the low minus high volatility portfolio underperforms the CAPM more severely if the portfolio is formed in the lower IO group.

The differential in the ICAPM alphas remains significant not because the idiosyncratic volatility discount was left unexplained in the lowest IO quintile (as it was unexplained by the CAPM and the Fama-French model). Panel B of Table 3 shows that FVIX in fact overexplains the idiosyncratic volatility discount. Adding FVIX reduces the alpha of the low minus high volatility portfolio in the lowest IO quintile from 1.18% per month, t-statistic 3.06, in the CAPM to 0.09% per month, t-statistic 0.36, in the ICAPM. However, the ICAPM alpha of the low minus high volatility portfolio in highest IO quintile is -0.59% per month, t-statistic -2.49, down from -0.045% per month, t-statistic -0.19, in the CAPM.

In the last pair of rows in Panel B, I look at the alphas and the FVIX betas of the low minus high volatility portfolio computed using the Fama-French model with FVIX. The results are similar: the difference in the alphas of the low minus high volatility portfolio in the lowest and the highest IO quintile is materially reduced compared to the conventional Fama-French model, but still remains sizeable and statistically significant. The source of the significance is primarily the negative alpha of the low minus high volatility portfolio in the highest IO quintile. The difference in the FVIX betas of the low minus high volatility portfolio in the lowest and the highest IO quintile confirms my idea that the idiosyncratic volatility discount decreases with IO because the exposure of the low minus high volatility portfolio to aggregate volatility risk does the same.

4.3 Turnover Effect

In Panel C of Table 3, I look at the turnover effect, defined as the difference in returns between the lowest and the highest turnover quintiles, in each IO quintile. In the top two rows I confirm the result in Nagel (2005), who finds that the CAPM alphas and the

Fama-French alphas of the low minus high turnover portfolio are significantly larger in the lowest institutional quintile. The difference in the CAPM alphas and the Fama-French alphas is 1% per month, t-statistic 3.29, and 0.8% per month, t-statistic 3.1, respectively.

In the next pair of rows, I find that adding the FVIX to the CAPM reduces the alpha differential to 0.46% per month, t-statistic 1.89. The key to the reduction is the difference in the FVIX betas of the low minus high turnover portfolio: their absolute value increases monotonically from -0.652, t-statistic -3.71, in the highest IO quintile, to -1.601, t-statistic -15.4, in the lowest IO quintile, signifying the corresponding increase in aggregate volatility risk. I conclude that the middle two rows of Panel C confirm my hypothesis that the turnover effect is stronger for low IO firms, because for these firms buying low turnover and shorting high turnover means more severe losses in response to unexpected increases in aggregate volatility and, consequentially, higher aggregate volatility risk.

In the last pair of rows, I come to the same conclusion using the Fama-French model with FVIX. The difference in the alphas between the low minus high turnover portfolios in the lowest and the highest IO quintiles becomes 0.49% per month, t-statistic 2.06, compared to the 0.8% per month difference, t-statistic 3.1, in the Fama-French alphas. The corresponding differential in FVIX betas is -2.345, t-statistic -5.98.

4.4 Analyst Disagreement Effect

Lastly, in Panel D of Table 3, I look at the analyst disagreement effect across the IO quintiles. I measure the analyst disagreement effect as the alpha differential between the lowest and the highest quintile formed on analyst forecast dispersion. The top two rows partially confirm the result in Nagel (2005): the alpha differential between the low minus high disagreement portfolio in the lowest and the highest IO quintile is 46.5 bp per month, t-statistic 1.83, in the CAPM, and 14 bp per month, t-statistic 0.7, in the Fama-French model. In his sample period, Nagel (2005) reports the CAPM alpha differential of 69 bp per month, t-statistic 1.92, and the Fama-French alpha differential of 50 bp per month, t-statistic 1.57. The difference in our results stems from the different sample periods: I look at the period between 1986 and 2006, and Nagel (2005) considers the period between 1980 and 2003. In unreported results, I find that the difference in our results arises almost exclusively because Nagel (2005) includes the 1980-1985 period, when the difference in the analyst disagreement effect between low and high IO firms was particularly strong.

In the next two rows, I estimate the two-factor ICAPM with the market factor and FVIX for the low minus high disagreement portfolio formed separately in each IO quintile. I find that, once I control for the FVIX factor, the difference in the analyst disagreement effect between the lowest and the highest IO quintile is only 2 bp per month, t-statistic 0.1. The FVIX factor is also able to explain the analyst disagreement effect in all IO quintiles, except for, probably, the highest quintile (t-statistic for the alpha is 1.88), which is consistent with Barinov (2009c). The key to the success is the difference in the FVIX betas of the low minus high disagreement portfolio between the lowest and the highest IO quintiles, which change from -0.343, t-statistic -2.1, in the lowest IO quintile to -1.131, t-statistic -7.91, in the highest IO quintile.

In the last pair of rows, I estimate the Fama-French model with FVIX for the low minus high disagreement portfolio formed separately in each IO quintile. I find that the alpha differential between the lowest and the highest institutional quintile is -8 bp per month, t-statistic -0.38, and the FVIX beta differential is -1.73, t-statistic -4.3, confirming the results from the middle two rows and my hypothesis that the analyst disagreement effect is stronger for low institutional firms, because for these firms sorting on analyst disagreement creates a wider spread in aggregate volatility risk.

5 IO and Future Returns

In this section, I test whether aggregate volatility risk can explain the positive relation between IO and future returns documented in Gompers and Metrick (2001), and the increase in the strength of this relation with market-to-book (Yan and Zhang, 2008) and uncertainty (Jiao and Liu, 2008).

The second regularity is easier to explain. The results in the previous two sections show that in the subsample of firms with low market-to-book (volatility) institutions prefer firms with higher market-to-book (volatility) and, consequentially, lower aggregate volatility risk. In the subsample of firms with high market-to-book (volatility) the reverse is true:

institutions pick the stocks with lower market-to-book (volatility) and higher aggregate volatility risk. Hence, the strategy of buying high and shorting low IO firms will result in negative exposure to aggregate volatility risk in the low market-to-book or low volatility subsample, and in positive exposure to aggregate volatility risk in the high market-to-book or high volatility subsample. Based on the difference in aggregate volatility risk alone I would therefore predict that the return differential between high and low IO firms will become more positive as either market-to-book or volatility increase.

On average, IO can be positively related to future returns if the relation between it and aggregate volatility risk is weakly negative or zero in the low market-to-book/volatility subsample and strongly positive in the high market-to-book/volatility subsample. As Panels A2 and B2 of Table 2 show, this is close to what happens in the data, where the relation between IO and aggregate volatility risk stays positive even if market-to-book and volatility are low. Also, in Table 1 I show that on average IO is negatively correlated with market-to-book and idiosyncratic volatility, which implies that on average IO should correlate positively with aggregate volatility risk.

5.1 IO Effect

In Table 4 I report the alphas and the FVIX betas of the IO quintile portfolios. To control for the size effects, the portfolios are formed using NYSE (exchcd=1) breakpoints and residual IO (see Nagel, 2005, and Section 2 of this paper for description). Using CRSP breakpoints makes the results stronger, using raw IO does not change them.

In the top two rows of Panel A (equal-weighted returns) and Panel B (value-weighted returns) I report the CAPM alphas and the Fama-French alphas. Consistent with Gompers and Metrick (2001), I find that the difference in the alphas between the highest and the lowest IO quintiles is between 25 bp and 50 bp per month, usually marginally significant.

An interesting result from Table 4 is that the positive relation between IO and future returns is driven exclusively by the underperformance of the low IO firms. This contrasts with the conclusion of Gompers and Metrick (2001) and other researchers, who establish the positive relation using cross-sectional regressions and interpret it as the evidence that institutions, on average, have the ability to pick the right stocks. Table 4 suggests that the real cause of the positive relation is the underperformance of the stocks ignored by institutions (the stocks in the bottom IO quintile have alphas between -20 bp and -30 bp per month, usually at least marginally significant), whereas there is no evidence that the stocks favored by institutions beat the CAPM or the Fama-French model (the alphas of the stocks in the top IO quintile are usually within one standard error from zero).

In the other rows I find that adding FVIX either to the ICAPM (the middle two rows) or the Fama-French model (the last two rows) reduces the differential to 0 bp to 15 bp, with t-statistics 1.1 and below. The alphas of the IO quintiles portfolios also stay within 20 bp and one standard error from zero. For example, in equal-weighted returns the CAPM alpha of the lowest IO quintile is -32 bp, t-statistic -1.79, and the ICAPM alpha is 7 bp per month, t-statistic 0.36.

The key to the success of the ICAPM are the FVIX betas: in equal-weighted returns, the difference in the FVIX betas between the lowest and the highest IO quintile is 0.628, t-statistic 4.99. Consistent with the pattern in the CAPM alphas, the FVIX betas are zero for high IO firms, but are significantly positive for low IO firms, suggesting that investors tolerate the low expected returns to these firms because these firms tend to beat the CAPM when aggregate volatility unexpectedly increases.

The last pair of rows looks at the alphas and the FVIX betas from the Fama-French model with FVIX. The conclusion is similar: controlling for aggregate volatility risk explains the alpha differential between the firms with the lowest and the highest levels of IO and explains the underperformance of firms with low IO. The explanation is the FVIX betas, which vary from 0.748, t-statistic 2.76, in the lowest IO quintile to -0.987, t-statistic -4.74, in the highest IO quintile, the difference being significant with t-statistic 4.15.

5.2 IO Effect and Market-to-Book

In Panel A of Table 5, I look at the IO effect on future returns across market-to-book quintiles. In each market-to-book quintile, I form an arbitrage portfolio that buys the highest and shorts the lowest IO quintile. The first two rows of Panel A report the CAPM alphas and the Fama-French alphas of this arbitrage portfolio.

I notice that the IO effect starts weak for value firms, but increases steadily with market-to-book, reaching the CAPM alpha of 93.5 bp per month, t-statistic 4.05, in the top market-to-book quintile. The difference in the IO effect between growth and value firms tops 50 bp per month and is significant in both CAPM and Fama-French alphas.

The evidence in the top two rows of Panel A is consistent with Yan and Zhang (2008), who use cross-sectional regressions to show that the positive relation between IO and future returns is stronger for growth firms. Yan and Zhang (2008) interpret this result as the evidence that institutional investors have comparative advantage in acquiring and processing information, and they are better able to make use of this comparative advantage in the case of growth firms, which are relatively hard to value.

However, Table 4 suggests that, contrary to the belief held in the literature, the IO effect does not mean stock picking ability of institutional investors. The puzzle is not why the stocks favored by institutional investors do so well - they do not, but why the stocks ignored by institutional investors underperform.

In untabulated results, I find that the increase of the IO effect with market-to-book is primarily driven by the deteriorating performance of low IO firms. The CAPM alpha of value firms with the lowest IO is 83 bp per month, t-statistic 2.68, compared to -69 bp per month, t-statistic -2.36 - the CAPM alpha of growth firms with the lowest IO. Moreover, the CAPM alpha of growth firms with the highest IO is only 25 bp per month, t-statistic 1.08. I conclude that the IO effect is stronger for growth firms not because institutional investors pick exceptionally good growth stocks, but because the growth stocks they ignore have abnormally low returns.

In Section 3, I show that institutional investors prefer value to growth, and this preference becomes more pronounced in the subsamples with higher market-to-book. Hence, as we move from value quintile to growth quintile, sorting stocks on IO creates a more and more negative sort on market-to-book (see Table 2, Panel A1 for confirmation). Because for growth firms sorting on IO means more negative spread in market-to-book, the respective difference in aggregate volatility risk becomes more positive and the IO effect becomes stronger. Also, growth firms ignored by institutions are ignored because their market-to-book is too high even for the growth subsample. But the high market-to-book means very low aggregate volatility risk (large and positive FVIX beta), which explains why the CAPM alpha of growth stocks with low IO is so negative.

In the middle two rows of Panel A, Table 5, I show that controlling for aggregate volatility risk explains why the IO effect increases with market-to-book and why it is so high for growth firms. The ICAPM alpha of the high minus low IO portfolio formed in the top market-to-book quintile is 45 bp per month, t-statistic 2.55, versus the similar CAPM alpha of 93.5 bp per month, t-statistic 4.05. In all other market-to-book quintiles the high minus low IO portfolio has insignificant ICAPM alphas. The difference in the alphas of the high minus low IO portfolio between top and bottom market-to-book quintiles is 24 bp per month, t-statistic 0.96, for the ICAPM, and 58 bp per month, t-statistic 2.27, for the CAPM.

The driving force behind the ICAPM results is the FVIX beta of the high minus low IO portfolio, which changes from -0.263, t-statistic -1.74, in the value quintile to -0.863, t-statistic -5.01, the difference being significant with t-statistic 2.29. In untabulated results I also find that in explaining the IO effect for growth stocks, FVIX hits right home with the FVIX beta of growth firms with the lowest IO at 1.63, t-statistic 10.3, which beats the FVIX beta of growth firms with the highest IO by more than 100%.

The FVIX betas of the low minus high IO portfolio show that buying high and shorting low IO firms becomes more profitable for the firms with higher market-to-book not because institutions are better in picking growth stocks, but because during increases in aggregate volatility this strategy trails the CAPM more severely if followed in the growth subsample. The reason for this underperformance is that in the effort to stay away from growth stocks, institutions forego important hedges against aggregate volatility risk, and they do it more in the growth subsample, where their desire to avoid high market-to-book stocks is the strongest (see Table 1 and Panel A1 of Table 2).

In the last two rows of Panel A, Table 5, I look at the alphas and FVIX betas from the Fama-French model with FVIX. The results are similar to the ICAPM: FVIX explains the difference in the IO effect between value and growth stocks, FVIX explains more than half of the large IO effect in top market-to-book quintile, and both results are backed up by significant FVIX betas.

5.3 IO Effect and Volatility

Jiao and Liu (2008) find that positive relation between IO and future returns is stronger for small stocks. Again, because the result comes from Fama-MacBeth regressions, Jiao and Liu (2008) conclude that this is the evidence of stock picking ability of institutional investors. If institutional investors have informational advantage, then it is natural to expect that they will thrive in the environment with significant uncertainty, which is characteristic of small stocks.

In Panels B to D, I look at the relation between the IO effect and the three variables related to firm-level uncertainty: idiosyncratic volatility (Panel B), turnover (Panel C), and analyst disagreement (Panel D). Consistent with Jiao and Liu (2008), I find that the IO effect is significantly higher if either of the three variables is high. In the sorts on idiosyncratic volatility, the difference in the IO effect between high and low volatility firms is around 1% per month and highly significant. In the sorts on turnover, the similar difference is around 0.9% per month and again highly significant. In the sorts on analyst disagreement, where the cross-sectional sample size is much smaller, the difference is 46.5 bp per month and marginally significant.

However, untabulated results show again that the stronger IO effect for the firms with high volatility/uncertainty exists because of the large underperformance of the firms with high volatility/uncertainty and low IO (CAPM alphas between -0.6% and -1.3% per month, highly significant), not because of the extremely good performance of the firms with high volatility/uncertainty and high IO (CAPM alphas between -25 bp and 45 bp per month, all insignificant). To put it differently, I find no evidence that in the high volatility subsample institutional investors demonstrate the ability to pick the right stocks. Rather, they stay away from the stocks that will do poorly according to the CAPM and the Fama-French model.

In Section 3, I show that institutional investors tend to prefer intermediate levels of volatility and ignore the stocks with extremely high and extremely low levels of volatility. Therefore, as Panel B of Table 2 confirms, in the high volatility subsample, sorting on IO implies reverse sorting on volatility and, consequentially, direct sorting on aggregate volatility risk. Thus, my explanation of the relation between the IO effect and volatility and why this relation is mostly driven by the underperformance of volatile stocks ignored by institutional investors, is the following: in the high volatility subsample, institutions tend to ignore the stocks with high levels of volatility and extremely high hedging ability against aggregate volatility risk. In the low volatility subsample they behave in the opposite way, and as a result in cross-section the exposure of the portfolio long in the highest and short in the lowest IO quintile to aggregate volatility risk increases with volatility.

In the middle rows of Panels B to D, Table 5, I look at the ICAPM alphas and FVIX betas of the portfolio long in the highest and short in the lowest IO quintile. I find that, compared to the CAPM, the two-factor ICAPM with the market factor and the FVIX factor reduces the difference in the alphas of this portfolio between the lowest and the highest volatility/uncertainty quintile by more than 50% and in all cases, except for Panel B (idiosyncratic volatility) makes the difference insignificant. The same is true about the ICAPM alphas of the low minus high IO portfolio in the highest volatility/uncertainty quintile: they decline by more than 50%, but remain significant in Panel B (idiosyncratic volatility) and Panel C (turnover).

I also find that the FVIX betas of the low minus high IO portfolio become significantly more negative as one moves from low to high volatility/uncertainty subsamples, which means that during unexpected increases in expected aggregate volatility the strategy of buying high and shorting low IO firms underperforms the CAPM significantly more, if the strategy is followed in the high volatility/uncertainty subsample. This is the reason why FVIX is capable of explaining the increase in the IO effect with volatility/uncertainty.

It is also important that the FVIX factor explains the cross-sectional dependence of the IO effect on volatility/uncertainty by tackling its underlying cause: the FVIX betas of the firms with the lowest IO and the highest volatility/uncertainty are by far the most positive in the five-by-five sorts on IO and volatility/uncertainty, and beat the FVIX betas of the firms with the highest IO and the highest volatility/uncertainty by a factor of three and more (results not reported to save space).

In the last two rows of Panels B through D I again look at the alphas and FVIX betas of the low minus high IO portfolio, but now the alphas and FVIX betas come from the Fama-French model with FVIX. The results are largely similar to what I have with the ICAPM in the middle two rows, confirming that in the high volatility/uncertainty subsample, high IO stocks beat low IO stocks not because institutional investors can pick future winners - they cannot, but because they ignore firms with extreme levels of volatility and consequent high ability to hedge against aggregate volatility risk, and these firms have low expected returns.

6 Robustness Checks

In this section, I perform two robustness checks of my main results. First, I replace FVIX by the change in VIX, which is the variable FVIX mimics, and check if this direct test confirms that the anomalies I look at (the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect) are indeed stronger for low IO firms because exploiting the anomalies means greater losses when aggregate volatility increases. I also use the change in VIX instead of FVIX to confirm that the positive relation between IO and future returns, as well as the increase in strength of this relation for growth firms and volatile firms are due to aggregate volatility risk.

Second, I look at the conditional CAPM and show that all return patterns described in the previous paragraph can be partly explained by the fact that the betas of the portfolios that try to exploit these patterns are countercyclical. To put it differently, the betas of the firms with high levels of volatility or growth options and low levels of IO tend to decrease sharply during recessions, which leads to the smaller increase in expected returns of these firms and the smaller loss of value compared to the firms with similar market betas.

The tests in this section use five arbitrage portfolios. The first portfolio, Inst, buys the firms from the top IO quintile and shorts the firms from the bottom IO quintile. The second portfolio, Inst MB, buys the analogue of the Inst portfolio formed in the top market-to-book quintile, and shorts the analogue of the Inst portfolio formed in the bottom market-to-book quintile. The other three portfolios: Inst IVol, Inst Turn, and Inst Disp, - are the same as Inst MB replacing the market-to-book with idiosyncratic volatility, turnover, and analyst forecast dispersion, respectively.

It is important to note that Inst MB measures two return patterns simultaneously:

the stronger IO effect for growth firms and the stronger value effect for low IO firms. To see it, denote the portfolio of firms with the highest level of IO and the highest level of market-to-book as HH, and the portfolio of the firms with the highest level of IO and the lowest level of market-to-book as HL. The LH and LL portfolios are defined similarly. Then Inst MB = (HH-LH) - (HL-LL), where (HH-LH) and (HL-LL) measure the IO effect in the top and bottom market-to-book quintile, respectively. Rearranging, we also see that Inst MB = (HH-HL) - (LH-LL), where (HH-HL) and (LH-LL) measure the value effect in the top and bottom IO quintile, respectively. The similar double interpretation applies to the other portfolios: Inst IVol, Inst Turn, and Inst Disp.

6.1 Aggregate Volatility Exposure

In Table 6, I regress daily returns to the five arbitrage portfolios (Inst, Inst MB, Inst IVol, Inst Turn, and Inst Disp) on the market factor and either the change in VIX (the leftmost column) or the FVIX factor (the second left column). I choose the daily frequency because at this frequency VIX is closer to the random walk, and therefore its change is a better proxy for the innovation in expected aggregate volatility, which is the variable of interest in the ICAPM context. I reestimate the ICAPM for daily returns to make sure that my results in the previous sections are robust to the change in the observation frequency. I also use both equal-weighted (left panel of Table 6) and value-weighted (right panel) returns.

The second left column with daily FVIX betas shows that changing the observation frequency from monthly to daily does not impact the results reported in the previous sections. All daily FVIX betas are negative, economically large, statistically significant, and reasonably close to the monthly FVIX betas. For example, the daily FVIX beta of the Inst Disp portfolio (equal-weighted returns, left panel of Table 6) is -0.713, t-statistic -12.5, and its monthly FVIX beta (Table 3, Panel D) is -0.788, t-statistic -8.17.

The leftmost column of both panels in Table 6 shows that in almost all cases one can replace FVIX by the change in VIX it mimics, and slope on the change in VIX will have the same sign and remain statistically significant. The only exception is the Inst IVol portfolio, which has an insignificantly positive loading on change in VIX in both equal-weighted and value-weighted returns. Also, in equal-weighted returns the Inst portfolio has zero loading on the VIX change, but the loading is reliably negative in value-weighted returns. In all other cases, the sign of the exposure to the VIX change is negative and significant in both columns.

Overall, the leftmost column shows significant exposure to innovations in expected aggregate volatility for all but one (Inst IVol) portfolios. Hence, the existence of the IO effect, its positive relation with market-to-book, turnover, and analyst forecast dispersion, as well as the positive relation between IO and the value effect, the turnover effect, and the analyst disagreement effect, can be explained by the fact that the portfolios trying to exploit these returns patterns significantly underperform the CAPM when expected aggregate volatility unexpectedly increases.

The magnitude of the slopes on the VIX changes seems to suggest that the impact of aggregate volatility on the arbitrage portfolios is moderate. VIX values are around 15 in expansions and can be over 40 in recessions[5]. Most slopes on the VIX change fall between -0.015 and -0.035, which implies that the arbitrage portfolios in Table 6 will underperform the CAPM by at most 50-120 bp as the economy goes all the way from expansion to recession. However, the regression of the market factor on the VIX change also yields a low, but highly significant coefficient of -0.13, implying that the market should drop by about 4% during recessions. I attribute the low coefficients to the fact that VIX can be a noisy estimate of the true expected aggregate volatility. This is supported by the evidence that FVIX betas have much higher t-statistics than the loadings on the VIX change.

In the two right columns, I report the slopes from pairwise regressions of the five arbitrage portfolios on the change in VIX or the FVIX factor (with the market factor omitted) to underscore the conditional nature of my results: I do not argue that when aggregate volatility increases, low IO firms or growth firms with low IO gain or that they beat high IO firms or value firms with low IO. All I show is that when aggregate volatility increases, low IO firms or growth firms with low IO, or other similar sort of firms perform significantly better than what the CAPM predicts.

Most loadings on FVIX and the VIX change in the two right columns are indeed either insignificant or have the wrong sign, confirming that firms with low IO, as well as growth

[5]VIX was 61.41 at the end of October 1987, going as high as 150.19 on October 19, 1987, and 61.38 at the end of October 2008, hitting 103.41 on October 10, 2008.

firms and high uncertainty firms with low IO, do not offer positive returns when aggregate volatility increases. Their returns in these periods are simply not as bad as the CAPM leads us to predict, hence their risk is lower than what the CAPM says, and this is the explanation of why these types of firms have negative alphas.

6.2 Conditional CAPM

In this subsection, I corroborate the previous results with the FVIX factor and the VIX change using the conditional CAPM. Prior research (Barinov, 2009a, 2009b, 2009c) shows that firms with abundant growth options and high levels of firm-specific uncertainty beat the CAPM when expected aggregate volatility increases. This effect has two causes. First, all else equal, the value of growth options, especially if the underlying asset is volatile, increases with volatility. Second, the beta of growth options decreases when uncertainty about the underlying asset increases, which usually happens simultaneously with increases in aggregate volatility (see Campbell, Lettau, Malkiel, and Xu, 2001, and Barinov, 2009c). In recessions, the decrease in the beta mutes the increase in expected returns and makes the corresponding value loss smaller.

In Section 3, I show that sorting on market-to-book and measures of firm uncertainty produces a wider spread in these measures in the low IO subsample, because institutions tend to avoid holding stocks with extreme levels of market-to-book and uncertainty. Therefore, while prior research (Barinov, 2009a, 2009b, 2009c) predicts that value minus growth portfolio, as well as the low minus high uncertainty portfolio, has countercyclical market betas (higher in bad times), I extend this prediction by arguing that these portfolios will have more countercyclical betas if formed in the low IO subsample, which partly explains why the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect are stronger in the low IO subsample. The flip side of this prediction is that the Inst portfolio will have more countercyclical betas if formed in the subsample of firms with high market-to-book or high uncertainty, and on average the betas of the Inst portfolio are countercyclical, which can potentially explain its positive alpha.

In Table 7, I estimate the conditional CAPM betas of the five arbitrage portfolios (Inst,

Inst MB, Inst IVol, Inst Turn, Inst Disp) by running the regression

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

where DIV_t is dividend yield of the CRSP value-weighted index over the past twelve months, DEF_t is the default premium, defined as the difference in yields between Aaa and Baa corporate bonds, TB_t is the one-month Treasury bill rate, and $TERM_t$ is the term premium, defined as the yield differential between ten-year and one-year Treasury bonds. I define the conditional beta as

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

In Table 7, I report the values of the conditional beta from (3) in recessions and expansions, along with the difference between the two, for the five arbitrage portfolios - Inst, Inst MB, Inst IVol, Inst Turn, and Inst Disp (the definitions are in the beginning of the section). I define recessions as the months when the expected market risk premium is above its in-sample median. The rest of the sample is labeled expansion. I estimate the expected market risk premium from

$$MKT_t - RF_t = \gamma_0 + \gamma_1 \cdot DIV_{t-1} + \gamma_2 \cdot DEF_{t-1} + \gamma_3 \cdot TB_{t-1} + \gamma_4 \cdot TERM_{t-1} + \epsilon_t \tag{4}$$

I expect the conditional betas of all portfolios to increase in recessions (which would mean positive values in the Diff column in Table 7), if the risk shift is a potential explanation of the stronger value effect, the stronger idiosyncratic volatility discount, the stronger turnover effect, and the stronger analyst disagreement effect for low IO firms, as well as a potential explanation of the IO effect and its positive dependence on market-to-book and uncertainty.

The Diff column in Table 7 indeed shows that both in equal-weighted and value-weighted returns the betas of all five arbitrage portfolio increase during recessions, contributing to the explanation of the positive alphas of these portfolios. All differences in betas are positive and significant. However, consistent with the Lewellen and Nagel (2006) critique, their magnitude ranges between 0.05 and 0.2, implying that even if the risk premium increases during recessions by 1% per month, the change in betas can explain 5 bp to 20 bp per month of the portfolio alphas, whereas the alphas range between 50 bp and 100 bp per month (see Table 3 and Table 4). The consequent inability of the conditional CAPM to explain the returns to the five arbitrage portfolios in Table 7 is further confirmed by the conditional CAPM alphas (not reported to save space), which decline by 10-15 bp compared to the unconditional CAPM alphas and remain significant.

The bottom line of the subsection is that the risk of the five arbitrage portfolios indeed moves in the predicted direction, thus partly explaining why firms with low IO and firms with high levels of uncertainty and market-to-book coupled with low IO beat the CAPM when aggregate volatility increases. However, the change in risk is insufficient to explain the magnitude of the returns to the five arbitrage portfolios, thus suggesting that one should abandon the conditional CAPM in favor of the ICAPM in explaining the stronger value effect, the stronger idiosyncratic volatility discount, the stronger turnover effect, and the stronger analyst disagreement effect for low IO firms, as well as the IO effect and why it is stronger for growth firms and high uncertainty firms.

7 Conclusion

The paper shows that aggregate volatility risk explains why several anomalies - the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect - are stronger for the firms with low IO. I document that institutional investors tend to ignore both the firms with extremely low levels of market-to-book and uncertainty (measured by either idiosyncratic volatility, or turnover, or analyst forecast dispersion) and the firms with extremely high levels of market-to-book and uncertainty. Institutional investors realize that they need some firm-specific uncertainty in their holdings to benefit from their comparative advantage in obtaining and processing information, and therefore they are reluctant to hold the stocks with very low levels of market-to-book, idiosyncratic volatility, turnover, and analyst disagreement. However, portfolio managers also tend to steer clear of the firms with high levels of volatility/uncertainty, because they cannot diversify away the impact of idiosyncratic risk on their compensation. Therefore, the firms with extreme levels of market-to-book, idiosyncratic volatility, turnover, and analyst disagreement are over-represented in the low IO subsample, and sorting on these variables in the low IO subsample creates a wider spread in these variables and, consequently, in aggregate volatility risk[6].

I find that the ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor) can explain more than 50% of the decrease in the magnitude of the four anomalies with IO, and the unexplained part is usually insignificant. I use both the FVIX factor, which is the factor-mimicking portfolio for the change in VIX, and the change in VIX itself to show that when aggregate volatility increases, the strategy that buys low and shorts high uncertainty firms trails the CAPM more severely if followed in the subsample of low IO firms. I also use the conditional CAPM to show that the market betas of this strategy increase more during recessions in the low IO subsample.

The fact that the firms with low uncertainty and low IO have the highest aggregate volatility risk, and the firms with high uncertainty and low IO have the lowest aggregate volatility risk also implies that buying high and shorting low IO firms means negative exposure to aggregate volatility risk if done in the low uncertainty subsample and positive exposure if done in the high uncertainty subsample. Hence, aggregate volatility risk can be an explanation of why the cross-sectional effect of IO on future returns is more positive for growth firms (Yan and Zhang, 2008) and for high uncertainty firms (Jiao and Liu, 2008). I show empirically that the two-factor ICAPM with the market factor and the FVIX factor indeed explains why the IO effect is stronger for growth firms and high uncertainty firms. I also use the change in VIX directly to show that when aggregate volatility increases, low IO firms beat high IO firms with similar market betas in the growth subsample and the high uncertainty subsample, but do not do so in the value subsample and the low uncertainty subsample. Moreover, the conditional market betas of the high minus low IO portfolio increase in recessions only in the growth subsample and the high uncertainty subsample.

I also find that positive exposure of the high minus low IO portfolio to aggregate volatility risk in the growth/high uncertainty subsample is much larger than the negative exposure of the same portfolio in the value/low uncertainty subsample. Hence, on average

[6]See Barinov (2009a) for the evidence that higher market-to-book and higher idiosyncratic volatility mean lower aggregate volatility risk and that aggregate volatility risk can explain the value effect and the idiosyncratic volatility discount. See Barinov (2009b) for similar evidence on turnover/turnover effect, and Barinov (2009c) for similar evidence on the analyst disagreement effect.

buying high IO firms and shorting low IO firms implies bearing aggregate volatility risk, which turns out to be sufficient to explain the positive alpha of this strategy. I also find that the positive cross-sectional relation between IO and future returns is driven exclusively by the negative alphas of the low IO firms, which is consistent with and successfully explained by the aggregate volatility risk story, but is inconsistent with the view of the positive cross-sectional relation between IO and future returns as the evidence that institutions have superior stock picking ability.

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] Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short Interest, IO, and Stock Returns, *Journal of Financial Economics*, v. 78, pp. 243-276

[3] Barinov, Alexander, 2009a, Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns, *Working Paper*, University of Georgia

[4] Barinov, Alexander, 2009b, Turnover: Liquidity or Uncertainty? *Working Paper*, University of Georgia

[5] Barinov, Alexander, 2009c, Anlayst Disagreement and Aggregate Volatility Risk, *Working Paper*, University of Georgia

[6] Bartov, Eli, Suresh Radhakrishnan, and Itzhak Krinsky, 2000, Investor Sophistication and Patterns in Stock Returns after Earnings Announcements, *Accouting Review*, v. 75, pp. 43-63

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

[8] 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, pp. 1-43

[9] Chen, Joseph, 2002, Intertemporal CAPM and the Cross-Section of Stock Returns, *Working Paper*, University of Southern California

[10] Collins, Daniel W., Guojin Gong, and Paul Hribar, 2003, Investor Sophistication and the Mispricing of Accruals, *Review of Accounting Studies*, v.8, pp. 251-276

[11] Datar, Vinay T., Narayan Y. Naik, and Robert Radcliffe, 1998, Liquidity and Stock Returns: An Alternative Test, *Journal of Financial Markets*, v. 1, pp. 203-219

[12] Del Guercio, Diane, 1996, The Distorting Effect of the Prudent-Man Laws on Institutional Equity Investments, *Journal of Financial Economics*, v. 40, 31-62

[13] Diether, Karl, Christopher Malloy, and Anna Scherbina, 2002, Differences of Opinion and the Cross-Section of Returns, *Journal of Finance*, v. 57, pp. 2113-2141

[14] Eric G. Falkenstein, 1996, Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings, *Journal of Finance*, v. 51, 111-135

[15] 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

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

[17] Fama, Eugene F., and James MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, v. 81, pp. 607-636

[18] Gompers, Paul A., and Andrew Metrick, 2001, Institutional Investors and Equity Prices, *Quarterly Journal of Economics*, v. 116, pp. 229-259

[19] Grullon, Gustavo, Evgeny Lyandres, and Alexei Zhdanov, 2007, Real Options, Uncertainty, and Stock Returns, *Working Paper*, Rice University and University of Lausanne

[20] Jiao, Yawen, and Mark H. Liu, 2008, Independent Institutional Investors and Equity Returns, *Working Paper*, Rensselaer Polytechnic Institute and University of Kentucky

[21] Lewellen, Jonathan, and Stefan Nagel, 2006, The Conditional CAPM Does Not Explain Asset-Pricing Anomalies, *Journal of Financial Economics*, v. 82, pp. 289-314

[22] Nagel, Stefan, 2005, Short Sales, IO, and the Cross-Section of Stock Returns, *Journal of Financial Economics*, v. 78, pp. 277-309

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

[24] Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance*, v. 52, pp. 35-55

[25] Yan Xuemin Sterling, and Zhe Zhang, 2008, Institutional Investors and Equity Returns: Are Short-Term Institutions Better Informed? *Working paper*, University of Missouri - Columbia and Singapore Management University

Table 1. IO, Uncertainty, and Growth Options

The table presents the results of firm-level Fama-MacBeth regressions of IO on market-to-book, or turnover, or idiosyncratic volatility, or analyst forecast dispersion (and their squares).

IO is the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP and reported in percentage. If the stock is on CRSP, but not on Thompson Financial 13F database, it is assumed to have zero IO. If the stock's capitalization is below the 20th NYSE/AMEX percentile, its IO is assumed to be missing.

Market-to-book is defined as market value of equity (Compustat item #25 times Compustat item #199) divided by book equity (Compustat item #60) plus deferred taxes (Compustat item #74). Turnover is trading volume divided by shares outstanding (both from CRSP). Turnover is measured monthly and averaged in each firm-year (at least 5 months with valid observations are required). NASDAQ (exchcd=3) turnover is divided by 2 to eliminate double-counting.

Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each month (at least 15 valid observations are required). Analyst disagreement is measured as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst excluded). Analyst disagreement is set to missing for the firms with stock price lower than $5.

The regressions also use the conventional controls: size, age, membership in the S&P500 index, stock price, cumulative returns in the past three months, cumulative return between month -4 and month -12, and dividend yield. All variables are percentage ranks and are computed before the start of the period for which IO is reported.

The breakpoint percentile at the bottom of each panel is the percentile of the corresponding independent variable, after which its slope changes from positive to negative.

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Separate Regressions

MB	-0.120	0.048	**Turn**	0.206	0.506
t-stat	*-24.8*	*3.86*	**t-stat**	*21.3*	*16.9*
MB2		-0.0016	**Turn2**		-0.0026
t-stat		*-16.3*	**t-stat**		*-12.2*
R-sq	0.242	0.244	**R-sq**	0.266	0.271
Adj. R-sq	0.241	0.243	**Adj. R-sq**	0.265	0.270
Controls	YES	YES	**Controls**	YES	YES
Breakpoint pctl=15			**Breakpoint pctl=97**		

IVol	-0.090	0.367	**Disp**	-0.004	0.046
t-stat	*-12.4*	*16.5*	**t-stat**	*-0.91*	*4.49*
IVol2		-0.0048	**Disp2**		-0.0005
t-stat		*-24.8*	**t-stat**		*-6.14*
R-sq	0.252	0.263	**R-sq**	0.251	0.252
Adj. R-sq	0.251	0.262	**Adj. R-sq**	0.250	0.251
Controls	YES	YES	**Controls**	YES	YES
Breakpoint pctl=38			**Breakpoint pctl=46**		

Panel B. Multiple Regressions

MB	-0.1112	0.0278	-0.1407	-0.0816	-0.1194	-0.0426
t-stat	*-25.2*	*2.27*	*-31.0*	*-5.45*	*-26.8*	*-2.92*
IVol	-0.1693	0.2108			-0.1804	0.1429
t-stat	*-23.9*	*9.73*			*-30.8*	*7.10*
Disp			-0.0224	0.0121	-0.0426	-0.0529
t-stat			*-5.31*	*1.27*	*-10.9*	*-6.41*
Turn	0.2670	0.4774			0.3337	0.5451
t-stat	*23.2*	*14.8*			*37.8*	*22.2*
MB2		-0.0013		-0.0006		-0.0007
t-stat		*-13.06*		*-4.23*		*-5.43*
IVol2		-0.0037				-0.0033
t-stat		*-16.4*				*-15.6*
Disp2				-0.0003		0.0001
t-stat				*-4.26*		*1.56*
Turn2		-0.0019				-0.0018
t-stat		*-9.32*				*-11.1*
Controls	YES	YES	YES	YES	YES	YES

Table 2. IO, Uncertainty, Growth Options, and Aggregate Volatility Risk

The table presents independent five-by-five double sorts on IO and market-to-book (Panel A) and IO and idiosyncratic volatility (Panel B). The sorting uses NYSE (exchcd=1) breakpoints. Market-to-book quintiles are rebalanced annually, IO quintiles are rebalanced quarterly, idiosyncratic volatility quintiles are rebalanced monthly.

The left part of Panel A (B) reports the medians of market-to-book (idiosyncratic volatility) for each of the 25 portfolios. The bottom row of each left panel reports the percentage change of the respective median characteristic between the lowest and the highest IO quintile. The right part reports the FVIX betas from the Fama-French model augmented by the FVIX factor. FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100.

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Market-to-Book and IO

Panel A1. Market-to-Book Ratios

	MB1	MB2	MB3	MB4	MB5	5-1
Inst1	0.833	1.327	1.844	2.630	5.774	4.941
t Inst1	*34.9*	*40.1*	*44.8*	*40.9*	*32.8*	*28.6*
Inst2	0.857	1.329	1.824	2.621	5.402	4.546
t Inst2	*37.1*	*42.3*	*42.8*	*40.7*	*35.9*	*30.6*
Inst3	0.863	1.325	1.815	2.618	5.040	4.177
t Inst3	*38.5*	*41.8*	*42.4*	*41.2*	*26.7*	*22.5*
Inst4	0.892	1.342	1.821	2.626	4.818	3.926
t Inst4	*38.0*	*41.4*	*44.2*	*39.6*	*30.2*	*25.6*
Inst5	0.902	1.343	1.832	2.624	4.847	3.945
t Inst5	*38.9*	*41.3*	*43.0*	*41.1*	*29.5*	*25.0*
1-5	-0.068	-0.016	0.012	0.006	0.927	0.995
t(1-5)	*-10.2*	*-3.67*	*2.83*	*0.70*	*19.7*	*20.7*
1-5	-8%	-1%	1%	0%	19%	25%

Panel A2. FVIX Betas

	MB1	MB2	MB3	MB4	MB5	5-1
Inst1	-0.232	0.223	0.104	0.573	1.649	1.881
t Inst1	*-0.63*	*0.86*	*0.56*	*2.01*	*6.58*	*4.69*
Inst2	-0.741	-0.459	-0.379	-0.092	0.978	1.719
t Inst2	*-2.28*	*-1.79*	*-1.58*	*-0.30*	*3.54*	*4.84*
Inst3	-0.675	-1.238	-0.977	-1.015	-0.076	0.599
t Inst3	*-2.96*	*-6.07*	*-4.12*	*-3.95*	*-0.29*	*1.52*
Inst4	-1.103	-1.645	-1.504	-1.265	-0.775	0.328
t Inst4	*-3.00*	*-6.32*	*-6.10*	*-5.42*	*-2.39*	*0.88*
Inst5	-1.187	-1.238	-1.609	-1.535	-1.081	0.105
t Inst5	*-4.25*	*-3.58*	*-5.79*	*-6.24*	*-3.30*	*0.35*
1-5	0.955	1.461	1.713	2.108	2.730	1.776
t(1-5)	*2.41*	*3.79*	*7.17*	*5.66*	*6.38*	*3.46*

Panel B. Idiosyncratic Volatility and IO

Panel B1. Idiosyncratic Volatility

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
Inst1	0.009	0.013	0.016	0.021	0.033	0.023
t Inst1	*32.0*	*32.9*	*36.6*	*35.2*	*31.6*	*29.1*
Inst2	0.009	0.013	0.017	0.021	0.031	0.022
t Inst2	*31.2*	*35.4*	*37.4*	*35.9*	*32.6*	*29.8*
Inst3	0.010	0.013	0.016	0.020	0.028	0.018
t Inst3	*32.3*	*35.7*	*37.2*	*36.4*	*31.7*	*28.6*
Inst4	0.011	0.014	0.016	0.020	0.026	0.015
t Inst4	*34.1*	*34.8*	*36.5*	*34.8*	*30.6*	*25.2*
Inst5	0.012	0.014	0.016	0.019	0.026	0.014
t Inst5	*33.7*	*33.5*	*35.3*	*34.1*	*29.8*	*23.9*
1-5	-0.002	-0.001	0.000	0.001	0.007	0.009
t(1-5)	*-19.6*	*-5.96*	*2.62*	*12.4*	*27.5*	*28.3*
1-5	-18%	-4%	2%	8%	28%	65%

Panel B2. FVIX Betas

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
Inst1	-0.771	-1.350	-1.100	-0.560	1.382	2.153
t Inst1	*-4.81*	*-10.11*	*-7.71*	*-2.82*	*6.03*	*6.92*
Inst2	-0.888	-1.039	-1.023	-0.814	0.880	1.768
t Inst2	*-6.86*	*-6.60*	*-5.13*	*-3.64*	*3.69*	*7.47*
Inst3	-1.258	-1.445	-1.331	-0.961	0.062	1.320
t Inst3	*-8.71*	*-8.01*	*-8.00*	*-3.92*	*0.27*	*5.47*
Inst4	-1.401	-1.618	-1.612	-1.522	-0.620	0.781
t Inst4	*-7.41*	*-9.15*	*-6.35*	*-4.78*	*-1.82*	*2.51*
Inst5	-1.650	-1.685	-1.705	-1.809	-0.695	0.955
t Inst5	*-7.84*	*-9.46*	*-7.09*	*-5.73*	*-2.16*	*2.69*
1-5	0.879	0.335	0.606	1.249	2.077	1.198
t(1-5)	*3.39*	*1.68*	*2.48*	*3.41*	*4.79*	*2.61*

Table 3. IO, Anomalies, and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas for the several anomalous arbitrage portfolios formed separately within each IO quintile. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX (ICAPM), and the Fama-French model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100.

The arbitrage portfolio in Panel A buys the stocks in the lowest market-to-book quintile and shorts the stocks with the highest market-to-book quintiles. The arbitrage portfolio in Panel B, (C, D) does the same with extreme idiosyncratic volatility (turnover, analyst forecast dispersion) quintiles.

All quintiles, including the IO quintiles, use NYSE (exchcd=1) breakpoints. Market-to-book and turnover quintiles are rebalanced annually, IO quintiles are rebalanced quarterly, idiosyncratic volatility and analyst disagreement quintiles are rebalanced monthly. The definition of all variables is in the heading of Table 1.

The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Value Effect and IO

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
$\boldsymbol{\alpha}_{CAPM}$	1.516	1.048	1.019	0.937	0.936	0.581
t-stat	*3.71*	*3.36*	*3.26*	*3.23*	*2.88*	*2.27*
$\boldsymbol{\alpha}_{FF}$	0.795	0.508	0.420	0.311	0.259	0.536
t-stat	*2.99*	*2.11*	*1.95*	*1.65*	*1.23*	*2.37*
$\boldsymbol{\alpha}_{ICAPM}$	0.563	0.409	0.449	0.350	0.321	0.242
t-stat	*2.03*	*1.64*	*1.90*	*1.69*	*1.40*	*0.96*
$\boldsymbol{\beta}_{FVIX}$	-1.690	-1.132	-1.011	-1.040	-1.090	-0.599
t-stat	*-6.67*	*-5.21*	*-6.68*	*-7.78*	*-8.09*	*-2.29*
$\boldsymbol{\alpha}_{FF4}$	0.556	0.378	0.423	0.284	0.198	0.358
t-stat	*2.22*	*1.53*	*1.85*	*1.52*	*0.98*	*1.59*
$\boldsymbol{\beta}_{FVIX}$	-1.859	-1.013	0.020	-0.205	-0.477	-1.382
t-stat	*-4.10*	*-2.54*	*0.06*	*-0.48*	*-1.43*	*-2.31*

Panel B. Idiosyncratic Volatility Discount and IO

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
$\boldsymbol{\alpha}_{CAPM}$	1.183	0.516	0.255	0.032	-0.045	1.228
t-stat	*3.06*	*1.61*	*0.88*	*0.12*	*-0.19*	*4.27*
$\boldsymbol{\alpha}_{FF}$	0.644	0.078	-0.194	-0.285	-0.269	0.913
t-stat	*2.87*	*0.41*	*-1.16*	*-1.64*	*-1.45*	*4.55*
$\boldsymbol{\alpha}_{ICAPM}$	0.087	-0.432	-0.665	-0.679	-0.594	0.681
t-stat	*0.32*	*-1.68*	*-2.61*	*-3.00*	*-2.49*	*3.60*
$\boldsymbol{\beta}_{FVIX}$	-1.943	-1.679	-1.630	-1.260	-0.973	-0.969
t-stat	*-14.8*	*-12.6*	*-10.2*	*-13.3*	*-10.2*	*-8.59*
$\boldsymbol{\alpha}_{FF4}$	0.332	-0.196	-0.392	-0.405	-0.357	0.688
t-stat	*1.65*	*-1.14*	*-2.69*	*-2.56*	*-2.00*	*3.41*
$\boldsymbol{\beta}_{FVIX}$	-2.426	-2.128	-1.543	-0.934	-0.681	-1.745
t-stat	*-7.20*	*-7.66*	*-5.38*	*-3.17*	*-2.30*	*-4.13*

Panel C. Turnover Effect and IO

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
$\boldsymbol{\alpha}_{CAPM}$	1.616	1.845	1.022	0.939	0.617	1.000
t-stat	*4.51*	*5.03*	*3.50*	*4.21*	*2.61*	*3.29*
$\boldsymbol{\alpha}_{FF}$	1.049	1.327	0.543	0.582	0.250	0.799
t-stat	*3.97*	*4.82*	*2.69*	*3.12*	*1.30*	*3.10*
$\boldsymbol{\alpha}_{ICAPM}$	0.713	0.998	0.325	0.521	0.249	0.464
t-stat	*2.87*	*3.90*	*1.61*	*2.86*	*1.27*	*1.89*
$\boldsymbol{\beta}_{FVIX}$	-1.601	-1.501	-1.235	-0.740	-0.652	-0.949
t-stat	*-15.4*	*-11.4*	*-13.1*	*-5.41*	*-3.71*	*-5.08*
$\boldsymbol{\alpha}_{FF4}$	0.760	0.999	0.364	0.561	0.274	0.486
t-stat	*3.03*	*3.84*	*1.85*	*2.90*	*1.42*	*2.06*
$\boldsymbol{\beta}_{FVIX}$	-2.247	-2.556	-1.391	-0.160	0.188	-2.435
t-stat	*-6.24*	*-5.41*	*-3.50*	*-0.41*	*0.48*	*-5.98*

Panel D. Analyst Disagreement Effect and IO

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
$\boldsymbol{\alpha}_{CAPM}$	1.096	0.643	0.547	0.595	0.631	0.465
t-stat	*3.61*	*2.51*	*2.31*	*2.88*	*2.68*	*1.83*
$\boldsymbol{\alpha}_{FF}$	0.834	0.526	0.471	0.601	0.692	0.142
t-stat	*3.34*	*2.15*	*2.06*	*2.93*	*3.00*	*0.70*
$\boldsymbol{\alpha}_{ICAPM}$	0.458	0.159	0.150	0.327	0.437	0.020
t-stat	*1.88*	*0.54*	*0.59*	*1.39*	*1.67*	*0.10*
$\boldsymbol{\beta}_{FVIX}$	-1.131	-0.858	-0.703	-0.475	-0.343	-0.788
t-stat	*-7.91*	*-4.27*	*-5.48*	*-3.92*	*-2.10*	*-8.17*
$\boldsymbol{\alpha}_{FF4}$	0.466	0.236	0.230	0.387	0.547	-0.081
t-stat	*2.24*	*1.10*	*1.12*	*2.02*	*2.39*	*-0.38*
$\boldsymbol{\beta}_{FVIX}$	-2.863	-2.254	-1.880	-1.663	-1.133	-1.730
t-stat	*-7.87*	*-5.23*	*-5.22*	*-5.81*	*-4.01*	*-4.30*

Table 4. IO Effect and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas of the IO quintile portfolios. The quintiles use NYSE (exchcd=1) breakpoints and are rebalanced quarterly. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX (ICAPM), and the Fama-French model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. Panel A looks at equal-weighted returns, Panel B considers value-weighted returns. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. Equal-Weighted Returns

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
α_{CAPM}	-0.318	-0.105	0.181	0.223	0.179	0.497
t-stat	*-1.79*	*-0.62*	*1.07*	*1.15*	*0.80*	*2.33*
α_{FF}	-0.250	-0.199	0.046	0.016	-0.003	0.247
t-stat	*-2.52*	*-2.65*	*0.58*	*0.17*	*-0.03*	*1.70*
α_{ICAPM}	0.067	0.095	0.284	0.243	0.209	0.142
t-stat	*0.36*	*0.50*	*1.54*	*1.23*	*0.97*	*1.10*
β_{FVIX}	0.682	0.354	0.182	0.035	0.053	-0.628
t-stat	*6.10*	*4.84*	*2.42*	*0.45*	*0.55*	*-4.99*
α_{FF4}	-0.156	-0.173	-0.024	-0.097	-0.169	-0.013
t-stat	*-1.59*	*-2.04*	*-0.31*	*-1.08*	*-1.63*	*-0.11*
β_{FVIX}	0.727	0.199	-0.547	-0.883	-1.293	-2.020
t-stat	*4.56*	*1.06*	*-3.26*	*-4.35*	*-7.94*	*-7.81*

Panel B. Value-Weighted Returns

	Low	**Inst2**	**Inst3**	**Inst4**	**High**	**1-5**
α_{CAPM}	-0.217	-0.020	0.149	0.099	0.065	0.282
t-stat	*-1.99*	*-0.25*	*1.71*	*1.30*	*0.60*	*1.44*
α_{FF}	-0.176	-0.064	0.039	0.064	0.120	0.296
t-stat	*-1.56*	*-0.78*	*0.50*	*0.78*	*1.36*	*1.68*
α_{ICAPM}	-0.116	-0.033	0.044	-0.012	0.009	0.125
t-stat	*-0.97*	*-0.41*	*0.53*	*-0.14*	*0.10*	*0.67*
β_{FVIX}	0.179	-0.023	-0.186	-0.197	-0.099	-0.278
t-stat	*1.72*	*-0.37*	*-3.84*	*-2.92*	*-0.92*	*-1.41*
α_{FF4}	-0.080	-0.021	-0.028	-0.001	-0.007	0.072
t-stat	*-0.61*	*-0.25*	*-0.36*	*-0.01*	*-0.09*	*0.38*
β_{FVIX}	0.748	0.332	-0.527	-0.509	-0.987	-1.736
t-stat	*2.76*	*1.80*	*-3.75*	*-3.82*	*-4.74*	*-4.15*

Table 5. IO Effect, Uncertainty, Growth Options, and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas of the arbitrage portfolio that buys the highest and shorts the lowest IO quintile. This arbitrage portfolio is formed separately in each market-to-book quintile (Panel A), each idiosyncratic volatility quintile (Panel B), each turnover quintile (Panel C), and each analyst disagreement quintile (Panel D). All quintiles use NYSE (exchcd=1) breakpoints. Market-to-book and turnover quintiles are rebalanced annually, IO quintiles are rebalanced quarterly, idiosyncratic volatility and analyst disagreement quintiles are rebalanced monthly. The definition of all variables is in the heading of Table 1. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, the CAPM augmented with FVIX (ICAPM), and the Fama-French model augmented with FVIX (FF4). FVIX is the factor-mimicking portfolio that tracks the daily changes in VIX, the implied volatility of one-month options on S&P 100. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Panel A. IO Effect and Market-to-Book

	Value	**MB2**	**MB3**	**MB4**	**Growth**	**5-1**
$\boldsymbol{\alpha}_{CAPM}$	0.354	0.444	0.474	0.525	0.935	0.581
t-stat	*2.01*	*2.29*	*2.74*	*2.47*	*4.05*	*2.27*
$\boldsymbol{\alpha}_{FF}$	0.168	0.294	0.380	0.339	0.704	0.536
t-stat	*0.91*	*1.70*	*2.18*	*1.77*	*3.97*	*2.37*
$\boldsymbol{\alpha}_{ICAPM}$	0.205	0.235	0.298	0.208	0.448	0.242
t-stat	*0.98*	*1.40*	*1.68*	*1.08*	*2.55*	*0.96*
$\boldsymbol{\beta}_{FVIX}$	-0.263	-0.370	-0.313	-0.562	-0.863	-0.599
t-stat	*-1.74*	*-4.11*	*-3.07*	*-3.88*	*-5.01*	*-2.29*
$\boldsymbol{\alpha}_{FF4}$	0.066	0.112	0.193	0.118	0.424	0.358
t-stat	*0.35*	*0.69*	*1.15*	*0.64*	*2.20*	*1.59*
$\boldsymbol{\beta}_{FVIX}$	-0.799	-1.419	-1.454	-1.719	-2.181	-1.382
t-stat	*-2.83*	*-6.57*	*-7.58*	*-6.18*	*-4.79*	*-2.31*

Panel B. IO Effect and Idiosyncratic Volatility

	Low	IVol2	IVol3	IVol4	High	5-1
$\boldsymbol{\alpha}_{CAPM}$	-0.053	-0.103	0.154	0.233	1.176	1.228
t-stat	*-0.37*	*-0.93*	*1.15*	*1.38*	*3.87*	*4.27*
$\boldsymbol{\alpha}_{FF}$	-0.056	-0.146	0.079	0.154	0.857	0.913
t-stat	*-0.41*	*-1.41*	*0.67*	*1.08*	*3.94*	*4.55*
$\boldsymbol{\alpha}_{ICAPM}$	-0.017	-0.122	0.106	0.108	0.664	0.681
t-stat	*-0.12*	*-1.17*	*0.83*	*0.81*	*3.47*	*3.60*
$\boldsymbol{\beta}_{FVIX}$	0.062	-0.035	-0.085	-0.223	-0.907	-0.969
t-stat	*0.85*	*-0.58*	*-0.92*	*-2.58*	*-6.68*	*-8.59*
$\boldsymbol{\alpha}_{FF4}$	-0.171	-0.220	-0.023	-0.007	0.518	0.688
t-stat	*-1.35*	*-2.15*	*-0.21*	*-0.06*	*2.78*	*3.41*
$\boldsymbol{\beta}_{FVIX}$	-0.895	-0.575	-0.792	-1.253	-2.641	-1.745
t-stat	*-4.48*	*-4.00*	*-3.95*	*-4.89*	*-7.81*	*-4.13*

Panel C. IO Effect and Turnover

	Low	Turn2	Turn3	Turn4	High	5-1
$\boldsymbol{\alpha}_{CAPM}$	0.144	0.468	0.280	0.633	1.143	1.000
t-stat	*0.89*	*2.01*	*1.09*	*2.24*	*3.66*	*3.29*
$\boldsymbol{\alpha}_{FF}$	0.011	0.215	0.037	0.255	0.810	0.799
t-stat	*0.08*	*0.98*	*0.16*	*1.18*	*3.53*	*3.10*
$\boldsymbol{\alpha}_{ICAPM}$	0.095	0.191	-0.103	0.020	0.559	0.464
t-stat	*0.56*	*0.89*	*-0.42*	*0.09*	*2.78*	*1.89*
$\boldsymbol{\beta}_{FVIX}$	-0.087	-0.490	-0.679	-1.087	-1.036	-0.949
t-stat	*-1.11*	*-4.69*	*-3.10*	*-6.32*	*-6.23*	*-5.08*
$\boldsymbol{\alpha}_{FF4}$	-0.040	0.002	-0.264	-0.069	0.446	0.486
t-stat	*-0.26*	*0.01*	*-1.26*	*-0.33*	*2.19*	*2.06*
$\boldsymbol{\beta}_{FVIX}$	-0.397	-1.659	-2.342	-2.517	-2.832	-2.435
t-stat	*-2.41*	*-7.04*	*-6.84*	*-7.85*	*-7.03*	*-5.98*

Panel D. IO Effect and Analyst Disagreement

	Low	Disp2	Disp3	Disp4	High	5-1
$\boldsymbol{\alpha}_{CAPM}$	-0.138	-0.148	0.139	-0.030	0.327	0.465
t-stat	*-0.85*	*-0.91*	*0.70*	*-0.12*	*1.15*	*1.83*
$\boldsymbol{\alpha}_{FF}$	-0.176	-0.155	0.040	-0.242	-0.034	0.142
t-stat	*-1.14*	*-1.10*	*0.24*	*-1.23*	*-0.17*	*0.70*
$\boldsymbol{\alpha}_{ICAPM}$	-0.233	-0.161	0.060	-0.297	-0.213	0.020
t-stat	*-1.60*	*-1.19*	*0.34*	*-1.52*	*-1.24*	*0.10*
$\boldsymbol{\beta}_{FVIX}$	-0.169	-0.023	-0.141	-0.472	-0.957	-0.788
t-stat	*-1.57*	*-0.19*	*-1.04*	*-3.51*	*-8.85*	*-8.17*
$\boldsymbol{\alpha}_{FF4}$	-0.321	-0.303	-0.142	-0.481	-0.402	-0.081
t-stat	*-2.13*	*-2.24*	*-0.84*	*-2.62*	*-2.54*	*-0.38*
$\boldsymbol{\beta}_{FVIX}$	-1.127	-1.152	-1.421	-1.853	-2.857	-1.730
t-stat	*-4.60*	*-4.91*	*-4.34*	*-4.45*	*-8.12*	*-4.30*

Table 6. IO, Anomalies, and Aggregate Volatility Exposure

The table reports the sensitivity to aggregate volatility changes of the anomalous arbitrage portfolios. The sensitivity is measured by estimating the following regressions:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta^{CAPM}_{\Delta VIX}} \cdot \Delta VIX \quad (5)$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta^{CAPM}_{FVIX}} \cdot FVIX \quad (6)$$

$$Ret = \alpha + \boldsymbol{\beta^{1f}_{\Delta VIX}} \cdot \Delta VIX \quad (7)$$

$$Ret = \alpha + \boldsymbol{\beta^{1f}_{FVIX}} \cdot FVIX \quad (8)$$

Inst is the portfolio long in the highest and short in the lowest IO quintile. Other portfolios measure the difference in the Inst portfolio returns between the highest and the lowest quintiles of the variables mentioned in their name. For example, Inst Turn is the return differential between the Inst portfolio formed in the highest turnover quintile and the Inst portfolio formed in the lowest turnover quintile. The detailed description of the variables is in the header of Table 1. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

	Equal-Weighted Returns					**Value-Weighted Returns**			
	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}		$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{1f}_{\Delta VIX}$	β^{1f}_{FVIX}
Inst	0.003	-0.325	0.007	-0.022	**Inst**	-0.021	-0.416	-0.028	-0.146
t-stat	*0.33*	*-5.31*	*0.90*	*-1.24*	**t-stat**	*-4.31*	*-5.58*	*-7.28*	*-9.67*
Inst MB	-0.035	-0.335	-0.049	-0.201	**Inst MB**	-0.014	-0.406	-0.021	-0.144
t-stat	*-5.61*	*-4.22*	*-8.90*	*-8.66*	**t-stat**	*-1.65*	*-4.04*	*-2.74*	*-4.45*
Inst IVol	0.020	-0.567	0.051	0.158	**Inst IVol**	0.007	-0.742	0.063	0.317
t-stat	*1.69*	*-7.30*	*3.71*	*4.17*	**t-stat**	*0.49*	*-4.60*	*4.07*	*7.10*
Inst Turn	-0.024	-0.609	-0.010	-0.024	**Inst Turn**	-0.071	-0.894	-0.011	0.254
t-stat	*-1.97*	*-8.25*	*-0.81*	*-1.16*	**t-stat**	*-6.51*	*-6.86*	*-1.18*	*5.41*
Inst Disp	-0.020	-0.713	0.019	0.166	**Inst Disp**	-0.035	-0.673	-0.001	0.114
t-stat	*-1.90*	*-12.5*	*1.52*	*7.79*	**t-stat**	*-4.27*	*-8.01*	*-0.13*	*4.10*

Table 7. IO, Anomalies, and Conditional CAPM

The table reports conditional CAPM betas across different states of the world for the arbitrage portfolio long in the highest and short in the lowest IO quintile (Inst portfolio), as well as the conditional CAPM betas of the arbitrage portfolios that measure the difference in the value effect (Inst MB), the difference in the idiosyncratic volatility discount (Inst IVol), the difference in the turnover effect (Inst Turn), and the difference in the analyst disagreement effect (Inst Disp) between the lowest and the highest IO quintiles. The detailed description of the variables is in the header of Table 1.

Recession (Expansion) is defined as the period when the expected market risk premium is higher (lower) than its in-sample median. The expected risk premiums and the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. The left panel presents the results with equal-weighted returns, and the right panel looks at value-weighted returns. The standard errors reported use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2006.

Equal-Weighted Returns				**Value-Weighted Returns**			
	Rec	**Exp**	**Diff**		**Rec**	**Exp**	**Diff**
Inst	0.181	-0.023	0.204	**Inst**	0.120	-0.074	0.194
t-stat	*7.57*	*-0.54*	*4.45*	**t-stat**	*4.24*	*-1.92*	*4.33*
Inst MB	0.020	-0.034	0.054	**Inst MB**	-0.066	-0.117	0.051
t-stat	*1.26*	*-1.40*	*1.97*	**t-stat**	*-4.49*	*-8.17*	*2.65*
Inst IVol	-0.224	-0.388	0.164	**Inst IVol**	-0.142	-0.386	0.244
t-stat	*-7.96*	*-8.74*	*3.30*	**t-stat**	*-6.57*	*-9.80*	*5.65*
Inst Turn	-0.124	-0.368	0.244	**Inst Turn**	-0.024	-0.448	0.424
t-stat	*-2.20*	*-5.59*	*3.07*	**t-stat**	*-0.47*	*-5.84*	*4.86*
Inst Disp	-0.179	-0.367	0.188	**Inst Disp**	-0.041	-0.213	0.172
t-stat	*-6.38*	*-7.69*	*3.58*	**t-stat**	*-2.91*	*-13.85*	*8.39*