Institutional Ownership and Aggregate Volatility Risk

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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). Institutions tend to stay away from the stocks with extremely low and extremely high levels of firm-specific uncertainty because of their desire to hedge against aggregate volatility risk or exploit their competitive advantage in obtaining and processing information, coupled with the dislike of idiosyncratic risk. Thus, the spread in uncertainty measures is wider for low IO stocks, and the same is true about the differential in aggregate volatility risk.

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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 effect (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.

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 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

[1]See, e.g., 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)

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.

Several recent papers (Barinov, 2011, 2013, 2014) show that higher firm-specific uncertainty and more option-like equity imply lower aggregate volatility risk. Barinov (2011) shows that an aggregate volatility risk factor (FVIX) explains the idiosyncratic volatility effect and the value effect, while Barinov (2013) and Barinov (2014) present similar evidence for the analyst disagreement effect and the turnover effect, respectively. All three papers also show that the negative effects of firm-specific uncertainty on expected returns are stronger for option-like (growth or distressed) firms and that this evidence is also explained by aggregate volatility risk.

The economic mechanism behind the evidence in Barinov (2011, 2013, 2014) is two-fold. First, firm-specific uncertainty increases when aggregate volatility goes up (see Campbell et al., 2001, and Barinov, 2013, for empirical evidence). One possible economic mechanism behind the comovement between average idiosyncratic risk and aggregate volatility is operating leverage. In recessions, when profit margins are low, a fixed absolute shock to input/output prices leads to a larger percentage change in profits, and thus a larger percentage change in expected cash flows and stock prices. This logic applies both to market volatility (if one considers market-wide shocks that affect every firm's profits) and (average) firm-specific volatility (if one considers firm-specific shocks to input/output prices).

Higher firm-specific uncertainty during periods of high aggregate volatility means that the value of option-like equity becomes less sensitive to the value of the underlying asset (because the delta of the option declines in volatility) and the option-like equity becomes therefore less risky precisely when risks are high. This effect is stronger for the firms with higher firm-specific uncertainty. Hence, firms with high firm-specific uncertainty and option-like equity 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, option-like equity increases in value when idiosyncratic volatility of the underlying asset increases (see Grullon, Lyandres, and Zhdanov, 2012, for empirical evidence). That makes the reaction of option-like equity to the increases of aggregate volatility (usually coupled with increases in idiosyncratic volatility) less negative. This effect is also stronger for firms with high idiosyncratic volatility, therefore such firms, especially if they are option-like, tend to lose less value than other firms with similar market betas when aggregate volatility and idiosyncratic volatility both increase.

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 firm-specific uncertainty and option-likeness. 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 dislike high aggregate volatility risk of the stocks with low levels of firm-specific uncertainty and option-likeness. 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 (considering them too dangerous). Sorting on uncertainty measures in the low IO subsample therefore produces the widest spreads in uncertainty and, consequently, aggregate volatility risk.

The observation that the link between firm-specific uncertainty and IO takes different signs for low and high values of uncertainty helps to resolve, for example, the puzzling positive relation between IO and firm-specific uncertainty observed by Gompers and Metrick (2001) and Yan and Zhang (2009) and contested by Falkenstein (1996) and Del Guercio. In my first empirical test, I observe that in the cross-sectional regressions of IO on measures of firm-specific uncertainty measures and controls the relation between firm-specific uncertainty and IO is indeed ambiguous and depends on research design. However, once I add the squared measures of uncertainty, a strong and uniform U-shaped relation between IO and uncertainty emerges.

Another important implication of the U-shaped relation between IO and uncertainty is that, as described above, the fact that many anomalies are stronger for low IO firms does not imply, as several existing studies claim, that these anomalies are mispricing. I show that the difference in aggregate volatility risk is enough to explain why the value effect, the idiosyncratic volatility effect, the turnover effect, and the analyst disagreement effect are stronger for the firms with low IO. When I look at the CAPM and Fama-French alphas, the difference in the magnitude of these four effects between the lowest and highest IO quintiles varies between 46 and 75 bp per month. However, in the two-factor ICAPM with the market factor and FVIX this difference is reduced by more than a half and usually becomes insignificant.

To further confirm that the stronger anomalies for low IO firms do not represent mispricing, I look at earnings announcement returns. While I do observe some concentration of the four anomalies I consider at earnings announcements (though only in equal-weighted returns), I do not normally observe any pronounced relation between this concentration and IO, inconsistent with the mispricing hypothesis.

The U-shaped relation between IO and uncertainty is also helpful in explaining the positive link between IO and future returns (henceforth, the IO effect). Gompers and Metrick (2001) is one of the first studies to document the IO effect. They ascribe the IO effect 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 (2009) and Jiao and Liu (2008) show that the IO effect is stronger for small stocks, growth stocks, and high uncertainty stocks, consistent with the argument in Gompers and Metrick (2001).

The evidence in Yan and Zhang (2009) 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 IO effect 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 the correlation between IO and aggregate volatility risk is 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.

Turning to earnings announcements again, I find that about one-third of the IO effect is concentrated at earnings announcements, but the concentration of the IO effect at earnings announcements does not depend on either firm-specific uncertainty or market-to-book. This evidence is largely consistent with the evidence from factor models that FVIX can explain up to 75% of the IO effect and 50-70% of its dependence on uncertainty/market-to-book.

The paper proceeds as follows. Section II describes the data sources. Section III 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 IV explains the relation between the anomalies and IO using the aggregate volatility risk factor. Section V 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 VI concludes.

2 Data and Preliminary Evidence

2.1 Data Sources

The data in the paper come from CRSP, Compustat, IBES, Thompson Financial, and the CBOE indexes databases. My main variable, 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 above the 20th NYSE/AMEX percentile, and missing IO otherwise.

Following Nagel (2005), in asset pricing tests that relate anomalies to IO, I use residual IO in order to eliminate the tight link between size and IO. Residual IO is the residual from

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

fitted to all firms within each separate quarter.

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 2012.

The definitions of all other variables are in the Data Appendix.

2.2 Aggregate Volatility Risk Factor

I define FVIX, my aggregate volatility risk factor, as a factor-mimicking portfolio that tracks 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 highly autocorrelated at the daily level, therefore its daily change is a suitable proxy for the innovation in expected aggregate volatility.

Following Ang, Hodrick, Xing, and Zhang (2006), I regress daily changes in VIX on daily excess returns to the five quintile portfolios sorted on past sensitivity to VIX changes. The sensitivity is the loading on the VIX change from the regression of daily stock returns in the past month on the market return and change in VIX. 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 VIX sensitivity quintiles to the ten industry portfolios (Fama and French, 1997) or the six size and book-to-market portfolios (Fama and French, 1993).

In order to be a valid and useful ICAPM factor, FVIX factor has to satisfy three requirements. First, it has to be significantly correlated with the variable it mimics (the change in VIX). In untabulated results, I find that the R-square of the factor-mimicking regression is 0.50, and the daily correlation between FVIX returns and VIX changes is expectedly high at 0.71. I conclude that FVIX clears the first hurdle of being a good mimicking portfolio.

Second, FVIX has to earn a sizeable and statistically significant risk premium, both in raw returns and, most importantly, on the risk-adjusted basis. Since FVIX is, by construction, positively correlated with VIX changes, FVIX represents an insurance against increases in aggregate volatility, and, as such, has to earn a negative risk premium. Untabulated results show that the average raw return to FVIX is -1.24 per month, t-statistic -3.73, and the CAPM alpha and the Fama-French alpha of FVIX are at -47 bp and -45 bp per month, t-statistics -4.33 and -3.63, respectively. I conclude that FVIX captures important risk investors care about, as the negative alphas suggest they are willing to pay a significant amount for the insurance against this risk provided by FVIX. Hence, FVIX clears the second hurdle for being a valid ICAPM factor.

Third, as Chen (2002) suggests, a valid volatility risk factor should be able to predict future volatility. Barinov (2013) shows that FVIX returns indeed predict several measures of expected and realized market volatility. Thus, FVIX clears the third and final hurdle for being a valid volatility risk factor.

Prior research shows that FVIX is useful in explaining several prominent anomalies: Barinov (2011) shows that FVIX can explain the value effect and the idiosyncratic volatility effect (the negative cross-sectional relation between idiosyncratic volatility and future returns). Barinov (2014) demonstrates that FVIX can explain the negative cross-sectional relation between turnover and future returns (the turnover effect), and Barinov (2013) shows that FVIX explains the analyst disagreement effect (lower future returns to firms with higher dispersion of analyst forecasts).

2.3 Firm-Specific Uncertainty and Sensitivity to Market-Wide Volatility Changes

The aggregate volatility risk explanation of the effects firm-specific uncertainty has on expected returns is based on two assumptions. First, average firm-specific risk and aggregate volatility have to comove, as Campbell et al. (2001) and Barinov (2013) show. Second, firm-specific risk of high-uncertainty firms should be more responsive to shifts in aggregate volatility, so that an increase in aggregate volatility would benefit those firms (through increasing the price and reducing the risk of their real options) more than low-uncertainty firms.

Table 1 performs two tests of the second hypothesis. First, if high-uncertainty firms respond by a stronger increase in uncertainty to market-wide shifts in volatility, the distribution of uncertainty across firms will become more dispersed in volatile periods of time. Panel A regresses cross-sectional standard deviation (Std) and quintile spread (Q3-Q1) of idiosyncratic volatility (IVol) and analyst disagreement (Disp) on measures of average firm-specific risk (average IVol and Disp) and measures of aggregate volatility: expected (VIX) and realized (average squared daily market return) and reports the slopes. For example, the top right cell contains the slope from a pairwise time-series regression of standard deviation of IVol, taken over the full cross-section of firms in each month, on average idiosyncratic volatility, computed in the same fashion.

Panel A finds uniformly across all measures (with a possible exception of the pair "volatility of analyst disagreement and realized market volatility") that as the economy as a whole becomes more volatile, measures of firm-specific risk also become more dispersed, which is consistent with the hypothesis in the paper that, as aggregate volatility increases, volatile firms become progressively more volatile.

Panels B and C of Table 1 present a different, more direct test that regresses change in individual firm's IVol or Disp on the change in VIX or realized market volatility or average IVol/Disp and then presents the median slope from this regression within each IVol/Disp quintile (the quintile are pre-sorted on the level of IVol/Disp in period t-1 and the regressions are run in period t). For example, the first line of Table 2R shows that a representative firm in the lowest IVol quintile (as of t-1) responds by 0.628% increase in idiosyncratic volatility to 1% increase in economy-wide average idiosyncratic volatility, while a representative firm in the highest IVol quintile responds by 1.182% IVol increase to a similar increase 1% in economy-wide idiosyncratic volatility.

The main result of Panels B and C is in its rightmost column, which shows that high IVol/Disp firms are more sensitive to changes in economy-wide volatility, irrespective of whether we measure economy-wide volatility as average IVol/Disp, VIX, or realized market volatility. The difference in the sensitivity to economy-wide volatility changes between high and low IVol/Disp firms is highly statistically significant (all t-stats are above 2.5) and economically sizeable (in the top panel, the sensitivity increases by an average of 50% between top and bottom IVol quintile, in the bottom panel it increases by an order of magnitude).

Overall, Table 1 confirms my hypothesis that firms with higher firm-specific uncertainty are more sensitive to economy-wide increases in volatility - their firm-specific uncertainty changes more in response and, if these firms are option-like (distressed or growth), their value should not decrease as much as their market beta would imply when market volatility increases.

3 Institutional Ownership and Firm Characteristics

3.1 Institutional Ownership, Firm-Specific Uncertainty, and Option-Like Equity

In this subsection, I establish the concave relation between IO and the variables related to firm-specific uncertainty and equity option-likeness by panel regressions with standard errors clustered by firm and by firm-year-quarter, as suggested in Petersen (2009).[4] Aside from these variables, I use the standard controls (not tabulated) 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.[5] All firm characteristics are measured in the quarter before the one for which IO is reported.

The hypothesis I am testing is that institutions are staying away from the firms with both extremely low and extremely high levels of firm-specific uncertainty. The reasons why institutions dislike high uncertainty 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 (a large fraction of her career earnings depends on the performance of her portfolio) and will thus avoid idiosyncratic volatility. Second, greater idiosyncratic volatility means a higher chance of facing withdrawals or margin calls and having to call off a 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 uncertainty. First, they arguably have comparative advantage in gathering and

[4]The results from more traditional Fama-MacBeth regressions (untabulated) are qualitatively similar.

[5]Some of the control variables, such as size and age, are presumably also correlated with uncertainty and equity option-likeness. In untabulated results, I find that the results in this section are robust to either dropping all controls or adding their squares.

processing information, and therefore need some uncertainty about the stock value in order to make use of this comparative advantage. Second, as Barinov (2011, 2013, 2014) shows, low uncertainty firms underperform the CAPM during periods of increasing expected aggregate volatility. Since such periods usually coincide with recessions and sharp market drops, risk-averse portfolio managers will try to avoid extra losses when aggregate volatility increases for the fear of increasing the already high risk of losing the job in recession.[6]

Similar argument can be made about equity option-likeness, which is 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 uncertainty (option-likeness) between the minimum and the maximum sample values of these variables. In other words, the regressions of IO on, e.g., 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.

In Panel A of Table 2, I regress IO on measures of firm-specific uncertainty and controls. All variables are transformed into percentage ranks to eliminate their extreme positive skewness.[7] The percentage ranks assign the value of 0 (N) to the firm with the lowest (highest) value of the characteristic, where N is the sample size, and then divide the

[6] It is intuitive that the relative strength of the countervailing effects of uncertainty on IO will depend on the level of uncertainty. For example, the ability of managers to benefit from higher uncertainty due to better information-processing ability is likely to exhibit diminishing returns as any technology, i.e., the same increase in uncertainty will be less useful if initial uncertainty is higher. Also, a cautious portfolio manager (more risk-averse than log utility) will have an increasingly strong desire to reduce uncertainty as uncertainty keeps going up. Thus, for high uncertainty stocks the portfolio manager's motives to reduce uncertainty will dominate, and vice versa.

[7] In untabulated results, I find that my main results are intact to using logs instead of ranks.

assigned values by N, to make sure that the ranked variable is always between 0 and 1.[8]

The first row that uses only the measures of uncertainty, without their squares, delivers mixed results on the IO-uncertainty link. The results seem to suggest that institutional investors prefer firms with high idiosyncratic volatility (Gompers and Metrick, 2001, report a similar puzzling result), but low analyst disagreement. Institutional investors strongly prefer high turnover firms, despite the evidence in Barinov (2014) that high turnover firms have higher uncertainty, but not necessarily higher liquidity. Also, institutional investors seem not to have a strong preference with respect to cash flow variability and analyst forecast errors. Both positive and negative coefficients are economically sizeable: the coefficient of -0.042 on analyst disagreement implies that as analyst disagreement increases from the 25th to 75th percentile, IO will decrease by $-0.042 \cdot (-0.5) = 2.1\%$ of shares outstanding, and similarly, an increase in turnover from the 25th to 75th percentile will result in a 17.3% increase in IO.

The next two rows of Panel A resolve the ambiguity observed in the first row by adding the squared measures of uncertainty to the regressions. Once the squared measures are added, the signs align for all five measures: the slope on the squared term is always negative and the slope on the non-squared term is always positive, suggesting that, consistent with my prediction, uncertainty is always positively related to IO if uncertainty is low, and the relation always becomes negative as uncertainty increases.

The last row of Panel A presents the percentiles at which the relation between IO and the uncertainty measure switches from positive to negative (computed as the top coefficient divided by two times the bottom coefficient). While the percentiles differ a lot across uncertainty measures, the change of the sign of the relation is observed for all five

[8]Note that the dependent variable, institutional ownership, is *not* transformed into ranks. Therefore, the panel regressions in Table 2 do not become rank regressions and standard OLS can be applied.

uncertainty measures. For example, the relation between IO and analyst forecast error (idiosyncratic volatility) changes from positive to negative when analyst forecast error (idiosyncratic volatility) exceeds 22th (60th) percentile.

The values of the coefficients in the middle two rows also suggest that the difference in the IO-uncertainty relation between low and high uncertainty firms is economically sizeable. For example, at the 10th cash flow volatility percentile, IO reacts by an increase of $0.152 - 2 \cdot 0.171 \cdot 0.1 = 0.118\%$ shares outstanding to the increase of cash flow volatility by one percentile. At the 90th volatility percentile, IO reacts by a decrease of $0.152 - 2 \cdot 0.171 \cdot 0.9 = -0.156\%$ shares outstanding to the increase of cash flow volatility by one percentile.

Panel B repeats the analysis using measures of equity option-likeness. Equity can be option-like either because the firm owns real options (growth firms) or because its equity is itself similar to a call option on the assets due to limited liability (distressed firms). Hence, the measures of option-likeness fall into two main categories: measures of financial distress and measures that classify a firm as a growth firm. I also use a catch-all measure of firm value convexity designed by Grullon, Lyandres, and Zhdanov (2012) - "SUE flex" - the loading on squared SUE from a firm-by-firm regression of earnings announcement returns on SUE and its square (detailed definitions of all variables are in the Data Appendix).

The first row of Panel B that does not use the squared measures of option-likeness arrives at mixed conclusions again. Consistent with prior research (see, e.g., Gompers and Metrick, 2001, Yan and Zhang, 2009), institutions tend to gravitate towards value firms, as indicated by significantly negative relation between IO and market-to-book, investment-to-assets, and sales growth. However, the link between IO and either R&D capital or SUE flex is non-existent. Measures of distress bring about an even more puzzling pattern: both credit rating and Z-score a puzzling tendency of institutional investors to prefer distressed firms[9], while O-score strongly suggests an opposite relation.

The next two rows of Panel B resolve the puzzles from the first row by adding the squared measures of option-likeness and finding that, just as in Panel A, the option-likeness measures always receive a significantly positive loading, whereas the coefficients on the squared terms are all significantly negative. Consistent with the preference for intermediate levels of volatility/uncertainty and the positive relation between volatility and option-likeness, the coefficients imply that institutions always prefer more option-like firms if the level of option-likeness is low, but then always switch to preferring less option-like firms in the subsample of highly option-like firms, effectively settling for firms with intermediate option-likeness just as they usually settle for an intermediate level of firm-specific uncertainty.

3.2 Aggregate Volatility Risk

The evidence in Table 2 suggests that, since institutions prefer stocks with intermediate levels of uncertainty and option-likeness, low IO subsample will be populated by firms with either very low or very high uncertainty/option-likeness. This observation is key to the main hypothesis in the paper of why several anomalies related to uncertainty and option-likeness are stronger for low IO firms: sorting low IO firms on uncertainty produces a wider spread in firm-specific uncertainty, equity option-likeness, and, consequently, aggregate volatility risk.

In Table 3, I test the hypotheses in the previous sentence by performing double sorts on residual IO (orthogonalized to size) and market-to-book, as well as on residual IO and idiosyncratic volatility. I resort to double sorts and residual IO because this is the research design used in the papers that use IO as a limits to arbitrage measure (see, e.g., Nagel,

[9] Credit rating is coded as AAA=1, AA+=2, ..., D=22, and Z-score, initially a measure of financial health, is multiplied by -1 to make it a measure of distress.

2005).

In the left part of Panel A, I sort firms into five quintiles on IO and market-to-book and report the median values of market-to-book for each portfolio. 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 11% 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 8% in terms of median market-to-book. As a result, the market-to-book differential between value and growth firms is by 13% 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 FVIX betas in Table 3 are from the two-factor ICAPM with the market factor and FVIX.

The right part of Panel A shows that the difference in FVIX betas between growth and value firms is 0.257, t-statistic 0.79, in the highest IO quintile and 1.236, t-statistic 2.40, 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, whereas the spread in FVIX betas is insignificant in the bottom three IO quintiles.

Looking down the columns of Panel A similarly reveals that IO is unrelated to aggregate volatility risk in the bottom three market-to-book quintile, but is negatively related to FVIX betas in the top two market-to-book quintiles, suggesting that aggregate volatility risk can be an explanation of why the positive relation between IO and future returns (the IO effect) is stronger for growth firms (as Yan and Zhang, 2009, show) and why the IO effect exists in the full sample. Again, the FVIX beta differentials and market-to-book differentials between low and high IO firms are not perfectly aligned with the market-to-book differentials in the left part of the panel, but the two differentials exhibit similar dynamics.

In Panel B, I look at the five-by-five sorts on idiosyncratic volatility and residual 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 25% 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 20%. Moreover, the differential in median idiosyncratic volatility between the highest and the lowest volatility quintiles is by whole 67% 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 in the double sorts. Similar to Panel A, I observe that the FVIX beta differential between the highest and lowest volatility quintile increases from 1.509, t-statistic 3.37, in the highest IO quintiles, to 2.361, t-statistic 4.04, in the lowest IO quintile, t-statistic for the difference 3.26. 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 effect is stronger for low IO firms.

Also, the FVIX beta differential between high and low IO quintiles switches from significantly positive in the low volatility quintiles to significantly negative in the high volatility quintiles (consistent with my story). I conclude that the FVIX factor is a potential explanation of the evidence in Jiao and Liu (2008) that the IO effect is stronger for high volatility firms.

4 Institutional Ownership, 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 effect, the turnover effect, and the analyst disagreement effect - are stronger for the firms with low IO.[10] Prior research (Barinov, 2011, 2013, 2014) shows that idiosyncratic volatility, market-to-book, turnover, and analyst disagreement are all negatively correlated with aggregate volatility risk, and this correlation explains their negative cross-sectional correlation with future returns (i.e., the anomalies in question). The hypothesis 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 Anomalies and Aggregate Volatility Risk

In the top two rows of each panel of Table 4, I confirm the results in Nagel (2005), who finds that the CAPM and Fama-French (1993) alphas of the strategies based on the four anomalies in question are significantly larger in the lowest IO quintile. The strategies in Table 4 short the top and buy the bottom quintile from the sorts on the respective variable (idiosyncratic volatility, market-to-book, etc.) The top two rows of all panels in Table 4 report that the anomalies are by 46 to 75 bp per month stronger in the lowest

[10]The previous section shows that there exists a U-shaped relation between IO and a much longer list of variables, many of which are also related to expected returns. The four anomalies studied in the paper were picked following Nagel (2005) and in the interest of brevity. Untabulated results (available from the author upon request) show very similar evidence using sales growth, investment, cash flow volatility, and the measures of financial distress.

IO quintile (the most common difference hovers around 70 bp per month). In most cases, the anomalies start relatively weak and often marginally significant in the top three IO quintiles, and then increase sharply in the bottom two IO quintiles, reaching, on average, 1% per month.[11]

In the bottom pair of rows, I report, for the same strategies, the ICAPM alphas and the FVIX betas from the ICAPM.[12] First, consistent with prior studies, I find that adding the FVIX factor uniformly reduces the anomalies in all IO quintiles either to almost zero (the idiosyncratic volatility and analyst disagreement effects) or roughly halves them and leaves at most marginally significant (the value and turnover effects).

Second, I confirm my main hypothesis that the stronger anomalies in the low IO subsample are largely explained by aggregate volatility risk. After I control for FVIX in the low IO subsample, the alphas of the low-minus-high strategies based on the anomalies decline by 50-90%. The largest decline is observed for the idiosyncratic volatility effect, for which the CAPM/ICAPM alpha in the lowest IO quintile is 1.27%/0.14% per month. The value effect in the low IO group witnesses the smallest, but still sizeable decline from 109 bp per month, t-statistic 2.87, to 56 bp per month, t-statistic 2.03.

Also, controlling for aggregate volatility risk drastically reduces the difference in the anomalies between high and low IO quintiles, from roughly 70 bp per month to roughly 30 bp per month and usually makes it insignificant. The only exception is the analyst disagreement effect, for which the difference in the effect between high and low IO firms declines from 75 bp per month, t-statistic 3.12, to 47 bp per month, t-statistic 2.14. It is of note, however, that in this case the significant difference between the ICAPM alphas is a difference between an insignificantly positive and insignificantly negative alpha.

[11] Controlling for additional factors like momentum, reversal, and liquidity does not materially change the results.

[12] Adding FVIX to the Fama-French model, the Carhart model, or other multi-factor models yields very similar results.

Third, I find, consistent with my hypothesis, that in the low IO subsample the strategies based on the anomalies have significantly more exposure to aggregate volatility risk. The difference in the FVIX betas of the strategies followed for low and high IO firms is between -0.6 and -1, which is quite large given that the CAPM alpha of FVIX is at -47 bp per month. The difference in FVIX betas is always statistically significant, and the FVIX betas of the strategies increase, in absolute magnitude, (almost) monotonically as one goes from high IO to low IO subsample.

In untabulated results (available upon request), I perform independent double sorts on IO and the four uncertainty measures to gauge the importance of short sale constraints. IO is presumably a better proxy for shorting fees than residual IO, and independent sorts break down the mechanical link between IO and anomalies' strength (in independent sorts, the spread in uncertainty does not vary as much across IO quintiles). I find that independent sorts on IO and uncertainty still produce the relation between IO and the four anomalies that is close in magnitude to what I observe in Table 4, and FVIX is still able to largely explain this relation, because the strategies based on the anomalies still load on FVIX significantly more negatively in the low IO subsample.

4.2 Earnings Announcement Effects

Table 4 shows that the stronger anomalies for low IO firms are largely explained by aggregate volatility risk. This evidence does not necessarily reject the existing mispricing explanations, usually based on investor sophistication or short-sale constraints. Table 4 just documents that, after controlling for risk properly, we cannot reject the hypothesis that the anomalies are not created by mispricing and the mispricing is not greater in the low IO subsample. That implies that the mispricing explanations seem to be redundant - one can explain the anomalies and their dependence on IO reasonably well without resorting to such explanations.

A more direct test of the mispricing explanations is to look at earnings announcement returns, as suggested, e.g., by LaPorta et al. (1997). Earnings announcements are a prime example of the time when a significant amount of firm-specific information hits the market. Thus, a significant amount of mispricing should be corrected around earnings announcements, as investors incorporate the information into the prices. Moreover, since the announcement window is short, only a trivial amount of the risk premium should be realized within the window, and almost all returns that accrue to a trading strategy during earnings announcements can therefore be classified as coming from resolution of mispricing.

In Table 5, I look at the earnings announcement returns of the strategies from Table 4. I compute the cumulative return between day t-1 (the day before the announcement) and day t+1 (the day after the announcement) and report both cumulative raw returns (EARet) and size and market-to-book adjusted returns (CAR). Since there is only one earnings announcement per quarter, one has to divide the numbers in Table 5 by three in order to compare them properly to the monthly alphas in Table 4.

The first thing I observe in Table 5 is that while there is some concentration of the anomalies at earnings announcements, it seems minor. According to Table 5, the largest return to a low-minus-high portfolio trading on an anomaly is 71 bp, which would be 23.7 bp on the monthly scale. Most announcement returns are 30 bp and below (10 bp on the monthly scale). Compared to the CAPM alphas of the same portfolios in Table 4, which normally range between 50 and 100 bp per month, the announcement returns are economically small, suggesting that the alleged mispricing captured by the anomalies in question is not realized around earnings announcements and thus there is probably no mispricing at all.

Second, a cursory look at Table 5 suggests that while earnings announcement returns to the anomalies are indeed greater in the low IO subsample, the difference in the announcement returns to the anomalies between high and low IO firms is usually statistically insignificant and economically minor. The only significant difference of 47 bp is observed when comparing the value effect for high and low IO firms, but that again translates to a monthly effect of 16 bp or about 30% of the respective CAPM alpha in Table 4. Similarly, as discussed in the previous paragraph, the earnings announcement returns to the anomalies in the low IO subsample (10-20 bp on the monthly scale) are just not large enough to contribute significantly to explaining the CAPM alphas of the anomalies in the low IO subsample (90-130 bp per month).

I conclude therefore that earnings announcement returns do not reveal a significant concentration of the anomalies at earnings announcements or a dependence of this concentration on IO. This evidence is consistent with the risk-based view of the anomalies and their relation to IO taken in the previous subsection, but appears inconsistent with the existing mispricing explanations.

5 Institutional Ownership and Future Returns

In this section, I test whether aggregate volatility risk can explain the positive relation between IO and future returns (the IO effect) documented in Gompers and Metrick (2001), and the increase in the strength of this relation with market-to-book (Yan and Zhang, 2009) and analyst disagreement (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 (disagreement) institutions prefer firms with higher market-to-book (disagreement) and, consequently, lower aggregate volatility risk. In the subsample of firms with high market-to-book (disagreement) 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 disagreement subsample, and in positive exposure to aggregate volatility risk in the high market-to-book or high disagreement 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 disagreement increase.

On average, IO can be positively related to future returns if the relation between IO 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 3 show, this is close to what happens in the data, where the relation between IO and aggregate volatility risk stays weakly positive even if market-to-book and volatility are low. Also, in Table 2, 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.[13]

5.1 IO Effect

In Table 6, I report the alphas and the FVIX betas of the IO quintile portfolios. 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

[13]A referee suggested an alternative reason why IO can be positively related to future returns: that can happen if sorting on IO picks up the factor structure that exists in, say, idiosyncratic volatility sorts. If this is the case, the IO effect will be the idiosyncratic volatility effect in disguise, and the high-minus-low return spread from IO sorts would "explain" the idiosyncratic volatility effect and vice versa. In untabulated results, I explored this possibility and found that the high-minus-low return spread from IO sorts cannot explain either of the anomalies mentioned in this paper or the FVIX alpha. The reverse is also true: the low-minus-high return spreads from idiosyncratic volatility/disagreement/turnover sorts cannot explain the IO effect. I conclude that the IO effect is not either of the uncertainty effects repackaged, and the fact that prior literature finds that FVIX can explain the anomalies mentioned in the paper does not automatically imply that FVIX can explain the IO effect.

Metrick (2001), I find that the difference in the alphas between the highest and the lowest IO quintiles is significantly positive, between 21 bp and 36 bp per month, with t-statistics between 1.78 and 2.55.

An interesting result from Table 6 is that the IO effect 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 IO effect using cross-sectional regressions and interpret it as the evidence that institutions, on average, have the ability to pick the right stocks. Table 6 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 -27 bp and -35 bp per month, usually highly significant. The portfolio sorts offer no evidence, however, 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 within 7 bp from zero.

In the next two rows, I find that using the ICAPM with FVIX reduces the alpha differential between high and low IO firms to less than 8 bp, with t-statistics below 1. 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 -0.64, t-statistic -2.28. Largely consistent with the pattern in the CAPM alphas, the FVIX betas are close to zero and sometimes even negative for high IO firms, but are significantly positive for low IO firms. The FVIX betas suggest that investors tolerate the low expected returns to low IO firms because these firms tend to beat the CAPM when aggregate volatility unexpectedly increases.

One can notice that the CAPM/FF alphas in Table 6 do not increase monotonically from bottom to top IO quintile, but rather form a U-shape that peaks in the third quintile. The same is true about ICAPM alphas, because FVIX betas are monotonically related to IO. In untabulated results, I look into this relation by first testing whether the alpha difference between quintiles three and five is statistically significant. I find that significance is present only in equal-weighted returns, which seems to suggest that, outside of small firms that dominate equal-weighted returns, the inverse U-shape in the IO quintiles alphas could have arisen by mere chance. I also look at a long list of firm characteristics across IO quintiles and found that the middle IO quintiles include somewhat more illiquid firms and value firms than other quintiles, which can explain their positive alphas.

In Panel C, I look at earnings announcements returns across the IO quintiles. Earnings announcements returns estimate the lower bound of part of the anomaly that should be attributed to mispricing. Earnings announcements returns are (almost) completely due to resolution of mispricing, since the realized risk premium at the announcements is very small because of the short period of time announcements take; however, mispricing can also be corrected outside of the earnings announcement window.

I find the earnings announcements return differential between low and high IO firms is comparable to the similar alpha differential in Panels A and B. Since alphas are monthly and earnings announcements happen once every three months, I conclude that at least one-third of the IO effect is mispricing.

The earnings announcements returns also agree with the evidence in Panels A and B that the IO effect is driven by low IO firms. For example, in the right part of Panel C (value-weighted returns) I observe that the announcement returns are flat between IO quintiles two and five and experience a sharp drop in the lowest IO quintile, which creates the whole IO effect in the earnings announcements returns. I conclude therefore that the IO effect is not driven by the stock-picking ability of institutional investors (and the failure of other investors to glean the value-relevant information from IO), but is most probably due to the overpricing of short-sale constrained, low IO firms in the spirit of Miller (1977).[14]

5.2 IO Effect, Market-to-Book, and Uncertainty

Table 7 looks at the IO effect across market-to-book (Panel A) and uncertainty (Panels B-D) quintiles. In each market-to-book/uncertainty quintile, I form an arbitrage portfolio that buys the highest and shorts the lowest IO quintile. The first two rows of each panel in Table 7 report the CAPM alphas and the Fama-French alphas of these arbitrage portfolios.

I notice that the IO effect starts weak for value and low uncertainty firms, but increases steadily with market-to-book and firm-specific uncertainty. Consistent with Yan and Zhang (2009), Panel A shows that the difference in the IO effect between growth and value firms is around 70 bp per month in both the CAPM and Fama-French alphas. The IO effect starts at 12-18 bp per month (insignificant) in the bottom two value quintiles and peaks above 80 bp per month (t-statistics greater than 4) in the top growth quintile.

Consistent with Jiao and Liu (2008), Panel D finds a similar pattern in analyst disagreement sorts. In the sample with at least two analysts covering the firm, the IO effect is limited to the top disagreement quintile and even becomes slightly negative for low disagreement firms. The difference in the IO effect between high and low disagreement firms stands at 61 bp per month, t-statistic 2.98, in the CAPM alphas and slightly less than that in the Fama-French alphas.[15]

Panels B and C use idiosyncratic volatility and turnover as alternative measures of disagreement and arrive at similar results: the IO effect is limited to one or two top disagreement quintiles, in which it normally tops 70 bp per month. The IO effect for high

[14]Miller (1977) argues that if a firm is costly to short, some pessimistic investors will be kept out of the market, and the market price will represent the average valuation of the firm by the remaining optimists. Miller predicts therefore that overvaluation will increase with the cost of selling short. Asquith, Pattak, and Ritter (2005) use IO as a proxy for supply of shares for shorting and argue that low IO is synonymous to costly short selling (and, therefore, overvaluation in the Miller (1977) model).

[15]Controlling for additional factors like momentum, reversal, and liquidity does not materially change the results.

disagreement (volatility, turnover) firms is then significantly stronger than the IO effect for low disagreement (volatility, turnover) firms. The only difference between Panels B and C, on the one hand, and Panel D on the other is that the IO effect is stronger overall in Panels B and C, since these panels do not restrict the sample to firms with two or more analysts necessary to compute the dispersion of earnings forecasts.[16]

In untabulated results, I find that the increase of the IO effect with market-to-book and disagreement is primarily driven by the deteriorating performance of low IO firms. I conclude, consistent with the evidence in Table 6, that the IO effect is stronger for growth and high disagreement firms not because institutional investors pick exceptionally good growth/high disagreement stocks, as the current literature argues, but because the growth/high disagreement stocks they ignore have abnormally low returns. This latter explanation is consistent with my main hypothesis that low IO firms include firms with both very low and very high values of market-to-book and uncertainty, and thus low IO firms with high market-to-book/uncertainty are the firms with extremely high market-to-book/uncertainty and consequently extremely low aggregate volatility risk.

In the bottom two rows of each panel in Table 7, I show that controlling for aggregate volatility risk explains why the IO effect increases with market-to-book and uncertainty and why it is so high for growth firms and high uncertainty firms. Controlling for FVIX reduces the difference in the IO effect between value and growth (high and low uncertainty) firms by about one-half and usually makes it insignificant. The largest decline in the difference happens in Panel B that reports the IO effect across idiosyncratic volatility quintiles: the difference goes from 64 bp per month, t-statistic 2.01, in the CAPM alphas to 19 bp per month, t-statistic 0.61, in the ICAPM alphas. The smallest decline happens in Panel A

[16]Yan and Zhang (2009) and Jiao and Liu (2008) also present evidence that the IO effect is stronger for smaller firms and firms with higher analyst forecast errors. While I stick to the four variables from the previous section for consistency, in untabulated results I also perform double sorts on IO and size, as well as on IO and forecast error, and arrive at results very similar to the ones presented in Table 7.

that does the same using market-to-book: the difference in the IO effect between growth and value firms changes from 70 to 41 bp per month and remains significant.[17]

Similarly, controlling for FVIX reduces the strong IO effect for high uncertainty/growth firms by about 50% and normally makes it insignificant. For example, the IO effect in the highest turnover (disagreement) quintile is at 83.5 (42) bp per month in the CAPM and 34 (8) bp per month in the ICAPM.

The FVIX betas in the bottom row of each panel also line up well with my hypothesis that the relation between the IO effect and uncertainty/market-to-book is driven by the institutions' preference for intermediate values of uncertainty/market-to-book. I see it more clearly in the top uncertainty/market-to-book quintiles, in which institutions stay away from high uncertainty/market-to-book firms (see Table 2 and Panel A1 of Table 3), thus creating a large negative spread in uncertainty/market-to-book between high and low IO firms. Since uncertainty and market-to-book are negatively related to aggregate volatility risk and positively related to FVIX betas due to the negative factor premium of FVIX (see Barinov, 2011, 2013, 2014, or the last row in each panel of Table 4), the negative spread in uncertainty/market-to-book results in a strongly negative spread in FVIX betas I observe in the fourth and fifth columns of each panel in Table 7.

In the bottom uncertainty/market-to-book quintiles the high-minus-low IO strategy is supposed to generate a positive spread in uncertainty/market-to-book and FVIX betas. The last columns of each panel in Table 7 do suggest that the FVIX betas of the high-minus-low IO portfolio are significantly more positive in the low uncertainty/market-to-book quintiles. However, with a possible exception of Panel B (idiosyncratic volatility sorts), the FVIX betas of the high-minus-low IO portfolio in the low uncertainty/value

[17]Adding FVIX to the Fama-French model, the Carhart model, or other multi-factor models yields very similar results.

quintiles are zero rather than positive. This is not entirely consistent with my hypothesis, but is not surprising given the evidence in Panels A1 and B1 of Table 3 that sorting low uncertainty/value firms on IO produces a mechanically smaller absolute spread in uncertainty/market-to-book than doing the same in the high uncertainty/growth subsample (in which the spread has the opposite sign).

5.3 IO Effect and Earnings Announcements

The previous subsection shows that at least 50% of the difference in the IO effect between high and low uncertainty (value and growth) firms is explained by aggregate volatility risk. The high-minus-low IO portfolio appears to trail the CAPM more severely in the times of increasing aggregate volatility if this portfolio is formed in the subsample of high uncertainty firms or growth firms, because in this subsample institutions gravitate towards firms with lower uncertainty/market-to-book and thus higher aggregate volatility risk. In the subsample of low uncertainty/growth firms, on the other hand, institutions exhibit the opposite behavior, which leads to small or even negative exposure to aggregate volatility risk.

The evidence in Table 7, however, does not reject the mispricing explanations of the stronger IO effect for high uncertainty and growth firms. Table 7 only states that, controlling for aggregate volatility risk, one cannot reject the null hypothesis that the performance of high IO firms relative to low IO firms is no different in high and low uncertainty (growth and value) subsamples.

In Table 8, I perform a cleaner test of whether the mispricing part of the IO effect is stronger for high uncertainty/growth firms by looking at earnings announcements. If the IO effect is indeed created by mispricing that becomes stronger for high uncertainty/growth firms, one will observe a strong concentration of the IO effect when the mispricing is partially corrected (at earnings announcements), especially in the high uncertainty and growth subsamples.

Table 8 shows, consistent with Table 6, that a visible part (roughly one-third) of the IO effect is indeed concentrated at earnings announcements. However, I observe little evidence that this concentration is stronger for high uncertainty firms or growth firms. In all but one cases the difference is statistically insignificant and remains within 40 bp (13 bp on the monthly scale). Compared to the similar difference in the monthly CAPM alphas in Table 7 (normally 60-70 bp per month), the difference between high and low uncertainty (growth and value) firm in the concentration of the IO effect at earnings announcements appears economically small.

I conclude that the risk-based explanation of why the IO effect is stronger for high uncertainty firms and growth firms seems to be more important than the mispricing explanations.

6 Robustness Checks

6.1 Anomalies, IO, and Exposure to Changes in VIX

The previous sections show that the low-minus-high portfolios that trade on the four anomalies (the value effect, the idiosyncratic volatility discount, the turnover effect, and the analyst disagreement effect) load negatively on FVIX, and even more so in the low IO subsample, which explains both the anomalies and their dependence on IO. Since FVIX, by construction, is positively correlated with VIX change (the correlation is 0.71 at daily frequency), the negative FVIX betas imply underperformance (negative CAPM/Fama-French alphas) when VIX increases.

In Panel A of Table 9, I use the VIX change directly to test whether the arbitrage portfolios that trade on either the four anomalies or the IO effect underperform when

VIX increases. I regress returns to arbitrage portfolios on the market factor and either change in VIX or FVIX (columns one and two) or the three Fama-French factors and either change in VIX or FVIX (columns three and four). Column five reports the CAPM market beta of the arbitrage portfolios. Since the autocorrelation in VIX is significantly higher at daily frequency, and thus daily change in VIX is closer to innovation in VIX than monthly change in VIX, Table 9 performs the analysis using daily returns.

Columns two and four report that all five arbitrage portfolios load negatively on FVIX in daily returns, thus establishing that my claim that the arbitrage portfolios are exposed to aggregate volatility risk is robust to using daily returns. Columns one and three replace daily FVIX with daily VIX changes and continue to find that the five arbitrage portfolios load significantly and negatively on VIX changes, thus confirming that the arbitrage portfolios trail the CAPM/FF model when VIX increases.

The fifth column reports the market betas of all arbitrage portfolios and finds that, except for the high-minus-low portfolio based on institutional ownership, all arbitrage portfolios have significantly negative market betas. The market betas allow estimating the economic importance of the slopes on change in VIX in the first and third columns. A similar regression of market returns on VIX changes yields the slope of -0.338 (on average, market drops by 33.8 bp when VIX increases by 1). A simple back-of-envelope calculation then suggests that, for example, IVol portfolio should gain, according to the CAPM, $0.582 \cdot 33.8$ bp ≈ 20 bp when VIX increases by 1. The first column, however, implies that IVol will gain 7.8 bp, or roughly 40%, less than that. Hence, the slope of IVol on VIX change is economically sizeable: it implies that, when VIX increases, IVol will gain 40% less than what the CAPM predicts.

The bottom panel of Table 4R looks at the difference in the returns of similar arbitrage portfolios formed in the low and high IO subsamples and finds similar results. The portfolios in the bottom panel load negatively both on FVIX and VIX change, and the magnitude of the loading on VIX change is economically and statistically significant. In other words, trading on the four anomalies exposes investors to significantly steeper losses in increasing VIX environment, if such trading is done in the low IO subsample.

In untabulated results, I also look at VIX change loadings across uncertainty/IO quintiles. I find that the loadings monotonically change from significantly positive for negative-alpha, high-uncertainty (or low IO) firms to significantly negative for positive-alpha, low-uncertainty (or high IO) firms, just as it should happen according to the aggregate volatility risk explanation of these anomalies. Likewise, in untabulated results I look at the VIX change loadings of the arbitrage portfolios that trade on the uncertainty anomalies in each IO quintile. The results generally fall into the mold of significantly negative loadings on VIX change in low IO quintiles (suggesting that trading on the anomalies in these quintiles implies suffering unexpectedly poor returns in increasing volatility environment) and insignificant or even positive loadings on VIX change for similar arbitrage portfolios in high IO quintiles (explaining why anomalies are insignificant in these quintiles: trading on the anomalies does not seem to imply volatility risk exposure in high IO quintiles).

6.2 Anomalies, IO, and Investor Sentiment

Baker and Wurgler (2006, 2007) argue that returns to high uncertainty firms are driven by investment sentiment. In particular, they show that high uncertainty firms become overvalued when sentiment is high. Hence, positive changes in sentiment will be associated with positive returns to such firms and negative returns to the low-minus-high arbitrage portfolios considered in the previous section.

In Table 10, I run a horse race between FVIX and the market sentiment measure of Baker and Wurgler (2006, 2007). The volatility risk explanation and the investor sentiment explanation of the four anomalies covered in the paper and their relation to IO are not mutually exclusive, thus the overlap between FVIX and sentiment may or may not be significant.

Table 10 uses the same arbitrage portfolios Table 9 uses and highlights three main results. First, I find no overlap between FVIX and sentiment changes. Both FVIX betas and sentiment betas do not change at all when the other factor is controlled for. This is true both when sentiment is orthogonalized to business cycle conditions as in Baker and Wurgler's papers ($Sent^{\perp}$) and when it is not orthogonalized. Second, I do find that the strategies based on the four anomalies in the paper have significant sentiment betas. The signs of the betas are consistent with the hypothesis of Baker and Wurgler that the short side of the strategies (firms with high turnover, or high idiosyncratic volatility, etc.) gains in response to sentiment increases. Third, the sentiment exposure of the strategies based on the four anomalies in the paper in indeed higher in low IO subsample (as it would be expected, if overpricing of high uncertainty stocks is stronger for low IO firms).

Overall, Table 10 suggests that while part of the four anomalies and their dependence on IO may be related to sentiment and therefore may be mispricing, the part of the four anomalies and their dependence on IO that is explained by FVIX appears to be risk-based, because FVIX has no apparent overlap with the sentiment indices of Baker and Wurgler. The same is true about the IO effect.

7 Conclusion

The paper shows that aggregate volatility risk explains why several anomalies - the value effect, the idiosyncratic volatility effect, 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 and extremely high levels of option-likeness or 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. However, portfolio managers also tend to steer clear of the firms with high levels of uncertainty, because, as Shleifer and Vishny (1997) point out, the managers cannot diversify away the impact of idiosyncratic risk on their compensation. Therefore, the firms with extreme levels of market-to-book and uncertainty 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[18].

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. The FVIX betas suggest 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 look at earnings announcement returns as an alternative test and find no significant extra concentration of returns at earnings announcements for the portfolios that trade on the four anomalies in the low IO subsample. This latter evidence suggests that there is no additional mispricing in the low IO subsample, and the concentration of the four anomalies in this subsample is likely to be risk-based.

The observation that the relation between IO and uncertainty/option-likeness is U-shaped also helps to explain puzzling and contradictory results on the relation between IO and uncertainty/option-likeness in the existing literature that assumes a linear relation. For example, contrary to the argument in Shleifer and Vishny (1997) and the evidence in Falkenstein (1996) and Del Guercio (1996), Gompers and Metrick (2001) and several other

[18] See Barinov (2011) 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 effect. See Barinov (2014) for similar evidence on turnover/turnover effect, and Barinov (2013) for similar evidence on the analyst disagreement effect.

recent papers find that IO increases with idiosyncratic volatility. I find that this result is, expectedly, sensitive to research design, and, most importantly, comes from an attempt to approximate a non-linear relation by a linear function.

The fact that the firms with high/low uncertainty and low IO have the lowest/highest aggregate volatility risk also implies that buying high and shorting low IO firms means negative (positive) exposure to aggregate volatility risk if done in the low (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, 2009) and for high uncertainty firms (Jiao and Liu, 2008).

I show empirically that the two-factor ICAPM with the market factor and FVIX indeed explains the IO effect in full sample, as well as why the IO effect is stronger for growth firms and high uncertainty firms. 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. Turning to earnings announcements, I do observe that about one-third of the IO effect is concentrated at earnings announcements, consistent with the IO effect partly being mispricing, but I do not find any sizeable difference in such concentration between high and low uncertainty (growth and value) firms. The latter evidence suggests that the cross-section of the IO effect is driven by risk rather than mispricing.

I also find that the IO effect 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 IO effect as the evidence that institutions have superior stock picking ability.

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A Data Appendix

CAR (earnings announcement returns) – size and book-to-market adjusted cumulative daily returns between the day prior to the earnings announcement and the day after the earnings announcement. Earnings announcement dates are from COMPUSTAT, daily returns are from CRSP daily files, size and book-to-market adjustment is performed following Daniel et al. (1997).

Cred (credit rating) – Standard and Poor's rating (splticrm variable in the Compustat quarterly file). The credit rating is coded as 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D.

CVCFO (cash flow volatility) - coefficient of variation (standard deviation over the average) of quarterly cash flows measured in the past 12 quarters. Cash flows are operating income before depreciation (oibdpq) less the change in current assets (actq) plus the change in current liabilities (lctq) less the change in short-term debt (dlcq) plus the change in cash (cheq). The cash flows are scaled by average total assets (atq) in the past two years. All variables are from the Compustat quarterly file.

Disp (analyst forecast dispersion) – the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst are excluded). Earnings forecasts are from the IBES Summary file.

EARet (earnings announcement returns) – cumulative raw daily returns between the day prior to the earnings announcement and the day after the earnings announcement. Earnings announcement dates are from COMPUSTAT, daily returns are from CRSP daily files.

Error (analyst forecast error) - the absolute value of the difference between the one-year-ahead consensus forecast and actual earnings divided by actual earnings. All variables are from the IBES Summary file.

IG (investment growth) - the change in capital expenditures (capx item from Compustat) in percentage of past-year capital expenditures: $IG_t = \dfrac{capx_t - capx_{t-1}}{capx_{t-1}}$.

IO (institutional ownership) – the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. If the stock is above the 20th NYSE/AMEX size percentile, appears on CRSP, but not on Thompson Financial 13F, it is assumed to have zero institutional ownership.

ITA (investment-to-assets) - the change in PPE (ppegt item from Compustat) plus the change in inventory (ppegt item from Compustat) in percentage of total assets (at Compustat item), calculated following Lyandres et al. (2008):

$$ITA_t = \frac{(PPE_t - PPE_{t-1}) + (INVENT_t - INVENT_{t-1})}{TA_{t-1}}. \tag{A-1}$$

IVol (idiosyncratic volatility) – 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). Average IVol is averaged for all firms within each month.

MB (market-to-book) – equity value (share price, prcc, times number of shares outstanding, csho) divided by book equity (ceq) plus deferred taxes (txdb), all items from Compustat annual files.

O-score - the probability of bankruptcy measure from Ohlson (1980), computed as

$$\begin{aligned} O = {} & -1.32 - 0.407 \cdot \ln TA + 6.03 \cdot \frac{TL}{TA} - 1.43 \cdot \frac{WC}{TA} + 0.076 \cdot \frac{CL}{CA} - 1.72 \cdot I(TL > TA) \\ & -2.37 \cdot \frac{NI}{TA} - 1.83 \cdot \frac{FFO}{TA} + 0.285 \cdot I(NI < 0 \;\&\; NI_{-1} < 0) - 0.521 \cdot \frac{NI - NI_{-1}}{|NI| + |NI_{-1}|}. \end{aligned} \tag{A-2}$$

where *TA* is the book value of total assets (Compustat item at), *TL* is the book value of total liabilities (lt), *WC* is working capital (wcap), *CL* are current liabilities (lct), *CA* are current assets (act), *NI* is net income (ni), NI_{-1} is the previous year net income, *FFO* are funds from operation (pi plus dp), $I(TL > TA)$ is the dummy variable equal to one if the book value of total liabilities exceeds the book value of total assets, and equal to zero otherwise, $I(NI < 0 \;\&\; NI_{-1} < 0)$ is the dummy variable equal to one if the net income was negative in the two most recent years, and equal to zero otherwise.

RD (research and development expenses) - R&D expenses (xrd item from Compustat) over total assets (at Compustat item).

RDCap (research and development capital) - weighted moving average of R&D expenses (xrd item from Compustat) over the past five years divided total assets (at Compustat item), calculated following Chan et al. (2001):

$$RDCap = \frac{RD_t + 0.8 \cdot RD_{t-1} + 0.6 \cdot RD_{t-2} + 0.4 \cdot RD_{t-3} + 0.2 \cdot RD_{t-4}}{TA_t}. \tag{A-3}$$

RIO (residual institutional ownership) – the residual (ϵ) from the logistic regression of institutional ownership (IO) on log Size and its square:

$$log(\frac{Inst}{1 - Inst}) = \gamma_0 + \gamma_1 \cdot log(Size) + \gamma_2 \cdot log^2(Size) + \epsilon. \tag{A-4}$$

Sent (investor sentiment) – is calculated according to the formula below

$$\begin{aligned} SENTIMENT_t = \quad & -0.241 \cdot CEFD_t + 0.242 \cdot TURN_{t-1} + 0.253 \cdot NIPO_t + \\ & +0.257 \cdot RIPO_{t-1} + 0.112 \cdot S_t - 0.283 \cdot P_{t-1}^{D-ND} \end{aligned} \tag{A-4}$$

where $CEFD_t$ is the closed-end fund discount (averaged across all closed-end funds traded in t), $TURN_{t-1}$ is average turnover across all firms in the market in t-1, $NIPO_t$ is the number of firms that went public in t, $RIPO_{t-1}$ is the first-day return to the IPOs placed in t-1, S_t is the share of equity issues in the amount of all security issues, P_{t-1}^{D-ND} is the log differential between the average market-to-book of dividend payers and dividend non-payers.

Size (market cap) – shares outstanding times price, both from the CRSP monthly returns file.

SG (sales growth) - the change in sales (sale item from Compustat) in percentage of last year sales: $SG_t = \dfrac{Sales_t - Sales_{t-1}}{Sales_{t-1}}$.

SUE flex is the slope (γ_2) from the firm-by-firm regression of earnings announcement returns on SUE squared (controlling for the level of SUE):

$$CAR_t = \gamma_0 + \gamma_1 \cdot SUE_t + \gamma_2 \cdot SUE_t^2 \tag{A-5}$$

The regression uses data from quarters t-1 to t-20 (at least 12 valid observations are required). Earnings announcement days are from Compustat quarterly file. Cumulative abnormal returns (CAR) are computed in the three days before, during, and after announcement using CAPM. The CAPM beta is estimated using daily returns in the year before the announcement. SUE is the difference between the announced EPS (epspiq over prccq lagged by one quarter) and average EPS in the past eight quarters, scaled by the standard deviation of EPS in the past eight quarters.

Turn (turnover) - monthly dollar trading volume over market capitalization at the end of the month (both from CRSP), averaged in each firm-quarter. I follow Gao and Ritter (2010) in adjusting the NASDAQ turnover to eliminate double-counting. I divide the NASDAQ turnover by 2.0 prior to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003, and leave it unchanged thereafter. Firms are classified as NASDAQ firms if the exchcd historical listing indicator from the CRSP events file is equal to 3.

Table 1. Volatility Sensitivity and Firm-Specific Uncertainty

Panel A reports the results of univariate regressions of standard deviation (Std) and quintile spread (Q3-Q1) of idiosyncratic volatility (IVol) and analyst disagreement (Disp) on average IVol, or average Disp, or VIX, or realized market volatility (average daily market return squared). All moments of IVol and Disp are computed in full cross-section within each month. Panel B and C sort firms on IVol and Disp, respectively, then perform firm-level univariate regressions of change in IVol/Disp on average IVol, or VIX, or realized market volatility (from Panel A), and then report the median slope for all firms in each quintile. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

Panel A. Volatility of Volatility and the Business Cycle

	$\overline{IVol}$	$\overline{Disp}$	VIX	$\overline{MKT^2}$
IVol Std	1.151	3.531	3.300	0.144
t-stat	*19.1*	*3.54*	*2.87*	*3.25*
IVol Q3-Q1	0.862	2.015	3.040	0.117
t-stat	*35.4*	*3.16*	*4.15*	*4.00*
Disp Std	13.98	6.876	1.019	1.821
t-stat	*2.40*	*13.53*	*2.40*	*1.28*
Disp Q3-Q1	1.341	0.379	0.105	0.260
t-stat	*3.48*	*15.0*	*2.46*	*1.69*

Panel B. Volatility Sensitivity across IVol Quintiles

	Low	IVol2	IVol3	IVol4	High	H-L
$\Delta\overline{IVol}$	0.628	0.770	0.860	0.970	1.182	0.553
t-stat	*40.3*	*56.4*	*58.8*	*75.6*	*85.5*	*26.1*
ΔVIX	0.011	0.012	0.013	0.013	0.015	0.004
t-stat	*6.37*	*6.35*	*6.15*	*5.85*	*5.28*	*2.71*
$\Delta\overline{MKT^2}$	0.099	0.123	0.132	0.145	0.168	0.069
t-stat	*18.1*	*17.3*	*17.3*	*17.7*	*15.6*	*8.94*

Panel C. Volatility Sensitivity across Disp Quintiles

	Low	Disp2	Disp3	Disp4	High	H-L
$\Delta\overline{Disp}$	0.116	0.080	0.225	0.559	2.572	2.457
t-stat	*4.43*	*5.64*	*8.79*	*10.4*	*34.7*	*31.1*
ΔVIX	-0.005	0.014	0.033	-0.002	0.155	0.160
t-stat	*-0.36*	*1.70*	*1.24*	*-0.06*	*2.91*	*3.03*
$\Delta\overline{MKT^2}$	0.107	0.156	0.078	0.015	1.181	1.074
t-stat	*1.52*	*2.63*	*0.64*	*0.07*	*3.11*	*2.85*

Table 2. Institutional Ownership, Uncertainty, and Growth Options

The table presents the results of panel regressions of IO on measures of firm-specific uncertainty and equity option-likeness. The measures are added one by one: Panels A1 and B1 report the slope on the measures themselves, Panels A2 and B2 add the squared measures as well. The breakpoint percentile at the bottom of each panel is the percentile of the corresponding independent variable, after which relation between the variable and IO changes from positive to negative. The regressions also use the conventional controls: size, age, membership in the S&P500 index, stock price, cumulative returns in the past three months, and cumulative return between month -4 and month -12. All variables are percentage ranks. The t-statistics in (curly) brackets use standard errors clustered by (firm-year-quarter) firm. The sample period is from January 1986 to December 2012.

Panel A. Institutional Ownership and Uncertainty

A1: γ from $IO_t = a + \gamma \cdot Unc_{t-1} + \delta \cdot Controls_{t-1}$

	IVol	**Disp**	**Turn**	**Error**	**CVCFO**
Var	0.194	-0.042	0.346	-0.010	-0.012
t-stat	(17.0)	(-4.71)	(34.7)	(-1.43)	(-0.98)
t-stat	{8.27}	{-3.79}	{19.8}	{-1.08}	{-0.95}
Controls	YES	YES	YES	YES	YES

A2: γ_1 and γ_2 from $IO_t = a + \gamma_1 \cdot Unc_{t-1} + \gamma_2 \cdot Unc^2_{t-1} + \delta \cdot Controls_{t-1}$

	IVol	**Disp**	**Turn**	**Error**	**CVCFO**
Var	0.956	0.036	1.021	0.031	0.152
firm t	(26.1)	(1.52)	(29.1)	(1.54)	(3.75)
2-way t	{12.9}	{1.37}	{15.4}	{1.51}	{3.77}
VarSq	-0.800	-0.082	-0.606	-0.043	-0.171
firm t	(-23.6)	(-3.64)	(-18.8)	(-2.21)	(-4.53)
2-way t	{-13.4}	{-3.34}	{-11.9}	{-2.22}	{-4.53}
Controls	YES	YES	YES	YES	YES
Break	60%	22%	84%	36%	44%

Panel B. Institutional Ownership and Option-Like Equity

B1: γ from $IO_t = a + \gamma \cdot Opt_{t-1} + \delta \cdot Controls_{t-1}$

	MB	RD	RDCap	IG	ITA	SG	SUEflex	Cred	O	Z
Var	-0.093	-0.164	-0.033	-0.034	-0.069	-0.056	-0.004	1.367	-0.054	0.005
t-stat	(-5.51)	(-10.2)	(-1.59)	(-6.86)	(-7.07)	(-6.21)	(-0.46)	(4.31)	(-4.14)	(0.35)
t-stat	{-7.78}	{-9.14}	{-1.73}	{-8.41}	{-8.16}	{-8.17}	{-0.46}	{4.32}	{-4.70}	{0.44}
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

A2: γ_1 and γ_2 from $IO_t = a + \gamma_1 \cdot Opt_{t-1} + \gamma_2 \cdot Opt^2_{t-1} + \delta \cdot Controls_{t-1}$

	MB	RD	RDCap	IG	ITA	SG	SUEflex	Cred	O	Z
Var	0.114	0.393	0.212	0.260	0.107	0.233	0.011	6.690	0.192	0.396
t-stat	(2.88)	(4.98)	(2.56)	(9.26)	(3.85)	(7.83)	(0.99)	(7.05)	(5.06)	(9.52)
t-stat	{2.46}	{5.01}	{2.58}	{8.66}	{3.81}	{7.12}	{1.00}	{6.96}	{4.46}	{8.97}
VarSq	-0.194	-0.515	-0.238	-0.290	-0.174	-0.283	-0.027	-29.357	-0.274	-0.418
t-stat	(-5.48)	(-7.56)	(-3.20)	(-10.44)	(-6.15)	(-9.58)	(-2.16)	(-6.33)	(-7.26)	(-9.89)
t-stat	{-5.07}	{-7.59}	{-3.23}	{-9.50}	{-5.95}	{-8.44}	{-2.20}	{-6.30}	{-6.44}	{-9.55}
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Break	29%	38%	45%	45%	31%	41%	20%	11%	35%	47%

Table 3. Institutional Ownership, Uncertainty, Growth Options, and Aggregate Volatility Risk

The table presents dependent five-by-five double sorts on first on residual IO and then on market-to-book (Panel A) or 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 two-factor ICAPM with the market factor and FVIX. 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 2012.

Panel A. Market-to-Book and Institutional Ownership

Panel A1. Market-to-Book Ratios

	MB1	**MB2**	**MB3**	**MB4**	**MB5**	**5-1**
RIO1	0.921	1.409	1.910	2.687	5.397	4.476
t-stat	*36.8*	*40.0*	*41.0*	*39.9*	*34.9*	*31.4*
RIO2	0.925	1.384	1.908	2.720	5.218	4.293
t-stat	*35.0*	*37.8*	*38.5*	*40.2*	*34.6*	*30.3*
RIO3	0.964	1.439	1.976	2.838	5.359	4.395
t-stat	*42.7*	*41.7*	*43.0*	*42.4*	*26.3*	*22.1*
RIO4	1.024	1.505	2.018	2.818	4.993	3.969
t-stat	*45.4*	*44.2*	*45.6*	*43.1*	*32.9*	*27.1*
RIO5	1.026	1.484	1.967	2.742	4.989	3.962
t-stat	*52.4*	*48.5*	*47.0*	*42.9*	*30.2*	*25.1*
1-5	0.106	0.075	0.057	0.055	-0.408	-0.513
t-stat	*7.69*	*3.22*	*1.51*	*0.96*	*-4.37*	*-5.85*
1-5	11%	5%	3%	2%	-8%	-13%

Panel A2. FVIX Betas

	MB1	**MB2**	**MB3**	**MB4**	**MB5**	**5-1**
RIO1	0.601	0.518	0.576	1.043	1.837	1.236
t-stat	*1.95*	*3.65*	*2.79*	*9.46*	*7.60*	*2.40*
RIO2	0.724	0.799	0.840	0.895	1.637	0.913
t-stat	*3.54*	*2.86*	*4.48*	*5.01*	*9.27*	*3.53*
RIO3	0.631	0.688	0.674	0.819	1.131	0.501
t-stat	*2.24*	*2.92*	*3.26*	*5.60*	*6.76*	*1.32*
RIO4	0.644	0.445	0.558	0.596	0.904	0.260
t-stat	*2.33*	*1.50*	*2.43*	*3.23*	*6.85*	*1.00*
RIO5	0.569	0.683	0.556	0.581	0.825	0.257
t-stat	*1.84*	*2.50*	*2.05*	*2.52*	*5.29*	*0.79*
1-5	-0.033	0.165	-0.020	-0.461	-1.012	-0.979
t-stat	*-0.29*	*0.99*	*-0.15*	*-2.20*	*-4.43*	*-4.14*

Panel B. Idiosyncratic Volatility and Institutional Ownership

Panel B1. Idiosyncratic Volatility

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
RIO1	0.91%	1.25%	1.56%	1.95%	2.83%	1.92%
t-stat	*28.5*	*27.8*	*31.1*	*32.1*	*30.4*	*28.5*
RIO2	0.91%	1.28%	1.61%	2.03%	2.83%	1.93%
t-stat	*31.5*	*30.1*	*31.4*	*32.3*	*29.5*	*25.9*
RIO3	1.03%	1.32%	1.59%	1.95%	2.56%	1.54%
t-stat	*32.4*	*33.4*	*35.8*	*35.9*	*29.7*	*25.1*
RIO4	1.13%	1.38%	1.58%	1.87%	2.40%	1.27%
t-stat	*29.9*	*32.1*	*34.4*	*33.4*	*29.0*	*22.8*
RIO5	1.20%	1.44%	1.62%	1.86%	2.36%	1.15%
t-stat	*31.1*	*31.3*	*32.4*	*32.3*	*28.1*	*21.1*
1-5	0.30%	0.19%	0.06%	-0.09%	-0.47%	-0.77%
t-stat	*22.0*	*18.12*	*4.40*	*-5.46*	*-21.83*	*-26.28*
1-5	25%	13%	4%	-5%	-20%	-67%

Panel B2. FVIX Betas

	IVol1	IVol2	IVol3	IVol4	IVol5	5-1
RIO1	-0.788	-0.651	-0.123	0.415	1.573	2.361
t-stat	*-3.35*	*-3.12*	*-0.85*	*2.56*	*4.34*	*4.04*
RIO2	-0.648	-0.568	-0.388	0.300	1.164	1.812
t-stat	*-2.67*	*-2.51*	*-1.94*	*1.75*	*3.64*	*3.30*
RIO3	-0.522	-0.477	-0.190	0.098	1.074	1.596
t-stat	*-2.21*	*-2.37*	*-0.69*	*0.54*	*4.35*	*3.72*
RIO4	-0.453	-0.446	0.064	0.068	0.810	1.262
t-stat	*-4.52*	*-2.34*	*0.55*	*0.44*	*4.70*	*5.21*
RIO5	-0.511	-0.257	0.318	-0.023	0.998	1.509
t-stat	*-4.20*	*-1.60*	*1.48*	*-0.12*	*2.46*	*3.37*
1-5	0.277	0.394	0.441	-0.437	-0.575	-0.852
t-stat	*1.23*	*2.10*	*2.41*	*-2.73*	*-2.55*	*-3.26*

Table 4. Institutional Ownership, Anomalies, and Aggregate Volatility Risk

The table reports the alphas and the FVIX betas for the several anomalous arbitrage portfolios formed separately within each residual IO quintile. The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, and the CAPM augmented with FVIX (ICAPM). 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 use NYSE (exchcd=1) breakpoints. Market-to-book quintiles are rebalanced annually, IO quintiles and turnover are rebalanced quarterly, idiosyncratic volatility and analyst disagreement quintiles are rebalanced monthly. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

Panel A. Value Effect and Institutional Ownership

	Low	**RIO2**	**RIO3**	**RIO4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	1.086	0.940	0.486	0.555	0.542	0.544
t-stat	*2.87*	*3.14*	*1.67*	*2.23*	*1.95*	*2.45*
$\boldsymbol{\alpha}_{FF}$	0.614	0.571	0.105	0.199	0.150	0.464
t-stat	*2.92*	*3.02*	*0.56*	*1.44*	*0.83*	*2.53*
$\boldsymbol{\alpha}_{ICAPM}$	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*
$\boldsymbol{\beta}_{FVIX}$	-1.236	-0.913	-0.501	-0.260	-0.257	-0.979
t-stat	*-2.40*	*-3.53*	*-1.32*	*-1.00*	*-0.79*	*-4.14*

Panel B. IVol Discount and Institutional Ownership

	Low	**RIO2**	**RIO3**	**RIO4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	1.273	0.721	0.493	0.496	0.563	0.710
t-stat	*3.57*	*2.13*	*1.84*	*2.35*	*1.98*	*2.14*
$\boldsymbol{\alpha}_{FF}$	0.908	0.392	0.231	0.103	0.191	0.717
t-stat	*4.52*	*2.68*	*1.69*	*0.76*	*1.33*	*3.86*
$\boldsymbol{\alpha}_{ICAPM}$	0.143	-0.126	-0.271	-0.119	-0.150	0.294
t-stat	*0.37*	*-0.38*	*-1.00*	*-0.55*	*-0.47*	*0.92*
$\boldsymbol{\beta}_{FVIX}$	-2.361	-1.812	-1.596	-1.262	-1.509	-0.852
t-stat	*-4.04*	*-3.30*	*-3.72*	*-5.21*	*-3.37*	*-3.26*

Panel C. Turnover Effect and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	1.203	1.115	0.657	0.552	0.481	0.722
t-stat	*3.88*	*3.49*	*2.76*	*2.58*	*2.26*	*3.07*
$\boldsymbol{\alpha}_{FF}$	0.944	0.817	0.411	0.331	0.272	0.672
t-stat	*4.19*	*4.03*	*2.52*	*2.03*	*1.52*	*3.07*
$\boldsymbol{\alpha}_{ICAPM}$	0.468	0.529	0.174	0.275	0.193	0.275
t-stat	*1.46*	*1.74*	*0.72*	*1.12*	*0.87*	*1.24*
$\boldsymbol{\beta}_{FVIX}$	-1.555	-1.261	-1.029	-0.583	-0.614	-0.941
t-stat	*-3.13*	*-2.78*	*-2.98*	*-1.88*	*-2.18*	*-3.68*

Panel D. AD Effect and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	0.880	0.410	0.384	0.343	0.127	0.753
t-stat	*3.48*	*1.74*	*1.59*	*1.82*	*0.58*	*3.12*
$\boldsymbol{\alpha}_{FF}$	0.796	0.376	0.395	0.392	0.209	0.588
t-stat	*3.72*	*1.83*	*1.80*	*2.28*	*1.04*	*2.92*
$\boldsymbol{\alpha}_{ICAPM}$	0.299	-0.115	-0.040	-0.077	-0.169	0.468
t-stat	*1.19*	*-0.43*	*-0.15*	*-0.39*	*-0.69*	*2.24*
$\boldsymbol{\beta}_{FVIX}$	-1.219	-1.113	-0.886	-0.874	-0.632	-0.587
t-stat	*-3.21*	*-3.45*	*-4.37*	*-5.00*	*-3.91*	*-1.96*

Table 5. Institutional Ownership, Anomalies, and Earnings Announcements

The table records average returns at earnings announcements of the arbitrage portfolios exploiting the anomalies named in the panels. EARet refers to raw returns, CAR designates size and book-to-market adjusted returns. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

Panel A. Value Effect and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
EARet	0.523	0.698	0.187	0.092	0.044	0.479
t-stat	*2.65*	*4.06*	*0.92*	*0.60*	*0.28*	*2.05*
CAR	0.423	0.551	0.143	-0.005	-0.042	0.465
t-stat	*2.28*	*3.37*	*0.75*	*-0.04*	*-0.27*	*2.02*

Panel B. IVol Discount and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
EARet	0.276	0.281	0.046	0.071	0.285	-0.009
t-stat	*2.11*	*2.96*	*0.44*	*0.60*	*1.74*	*-0.05*
CAR	0.371	0.235	0.050	0.127	0.293	0.079
t-stat	*3.33*	*2.63*	*0.48*	*1.08*	*1.96*	*0.47*

Panel C. Turnover Effect and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
EARet	0.498	0.710	0.007	0.172	0.216	0.283
t-stat	*3.21*	*5.35*	*0.06*	*1.75*	*1.32*	*1.25*
CAR	0.430	0.677	0.025	0.171	0.107	0.322
t-stat	*2.82*	*5.42*	*0.19*	*1.69*	*0.69*	*1.51*

Panel D. AD Effect and Institutional Ownership

	Low	RIO2	RIO3	RIO4	High	L-H
EARet	0.401	0.277	0.198	0.032	0.265	0.136
t-stat	*2.65*	*1.83*	*1.36*	*0.14*	*1.57*	*0.65*
CAR	0.305	0.267	0.280	0.022	0.304	0.002
t-stat	*2.05*	*2.05*	*2.17*	*0.10*	*1.98*	*0.01*

Table 6. Institutional Ownership Effect and Aggregate Volatility Risk

Panels A and B report 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, and the two-factor ICAPM with the market factor and FVIX. 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 C reports the average returns of the high-minus-low IO portfolios at earnings announcements (raw, EARet, and size-MB-adjusted, CAR). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

Panel A. Equal-Weighted Returns

	Low	Inst2	Inst3	Inst4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	-0.315	0.065	0.181	0.203	0.040	0.355
t-stat	*-1.85*	*0.42*	*1.21*	*1.30*	*0.25*	*2.11*
$\boldsymbol{\alpha}_{FF}$	-0.350	-0.012	0.069	0.078	-0.066	0.284
t-stat	*-4.49*	*-0.18*	*0.92*	*0.83*	*-0.66*	*2.15*
$\boldsymbol{\alpha}_{ICAPM}$	0.068	0.347	0.361	0.322	0.129	0.061
t-stat	*0.34*	*1.85*	*2.16*	*2.04*	*0.81*	*0.39*
$\boldsymbol{\beta}_{FVIX}$	0.829	0.604	0.385	0.253	0.188	-0.640
t-stat	*3.72*	*3.19*	*3.79*	*1.89*	*1.43*	*-2.28*

Panel B. Value-Weighted Returns

	Low	Inst2	Inst3	Inst4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	-0.273	-0.008	0.153	0.079	-0.064	0.208
t-stat	*-3.18*	*-0.11*	*1.95*	*1.20*	*-0.93*	*1.78*
$\boldsymbol{\alpha}_{FF}$	-0.296	-0.040	0.082	0.059	-0.014	0.282
t-stat	*-3.44*	*-0.52*	*1.22*	*0.87*	*-0.23*	*2.55*
$\boldsymbol{\alpha}_{ICAPM}$	-0.203	0.051	0.120	0.026	-0.124	0.079
t-stat	*-2.18*	*0.62*	*1.45*	*0.35*	*-1.93*	*0.64*
$\boldsymbol{\beta}_{FVIX}$	0.163	0.119	-0.066	-0.111	-0.130	-0.293
t-stat	*2.11*	*1.88*	*-0.45*	*-1.95*	*-1.79*	*-3.19*

Panel C. Earnings Announcements

C1. Equal-Weighted Returns

	Low	Inst2	Inst3	Inst4	High	L-H
EARet	0.103	0.197	0.375	0.524	0.401	0.298
t-stat	*1.36*	*3.06*	*5.77*	*5.36*	*3.83*	*3.54*
CAR	-0.091	-0.035	0.145	0.299	0.228	0.319
t-stat	*-2.06*	*-1.01*	*3.74*	*5.40*	*3.73*	*3.73*

C2. Value-Weighted Returns

	Low	Inst2	Inst3	Inst4	High	L-H
EARet	-0.110	0.379	0.394	0.378	0.342	0.451
t-stat	*-0.77*	*3.36*	*5.43*	*3.48*	*2.99*	*3.26*
CAR	-0.184	0.207	0.179	0.226	0.187	0.372
t-stat	*-1.30*	*2.42*	*2.03*	*3.21*	*2.26*	*2.72*

Table 7. Institutional Ownership 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 following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, and the two-factor ICAPM with the market factor and FVIX. 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 2012.

Panel A. IO Effect and Market-to-Book

	Low	**MB2**	**MB3**	**MB4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.174	0.181	0.416	0.637	0.877	0.702
t-stat	*1.25*	*1.50*	*2.44*	*2.98*	*4.52*	*3.67*
$\boldsymbol{\alpha}_{FF}$	0.132	0.120	0.353	0.540	0.806	0.674
t-stat	*0.96*	*1.05*	*2.24*	*3.06*	*4.70*	*4.24*
$\boldsymbol{\alpha}_{ICAPM}$	0.089	0.168	0.317	0.414	0.496	0.408
t-stat	*0.68*	*1.37*	*1.85*	*2.25*	*2.89*	*2.26*
$\boldsymbol{\beta}_{FVIX}$	-0.193	-0.017	-0.230	-0.477	-0.805	-0.612
t-stat	*-2.28*	*-0.14*	*-1.01*	*-1.91*	*-3.51*	*-2.43*

Panel B. IO Effect and Idiosyncratic Volatility

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.067	-0.089	0.212	0.264	0.704	0.637
t-stat	*0.38*	*-0.53*	*1.18*	*1.08*	*2.29*	*2.01*
$\boldsymbol{\alpha}_{FF}$	0.020	-0.145	0.142	0.205	0.675	0.655
t-stat	*0.12*	*-0.88*	*0.69*	*0.78*	*2.38*	*2.12*
$\boldsymbol{\alpha}_{ICAPM}$	0.188	0.061	0.094	0.041	0.376	0.188
t-stat	*0.94*	*0.41*	*0.52*	*0.17*	*1.34*	*0.61*
$\boldsymbol{\beta}_{FVIX}$	0.268	0.312	-0.263	-0.470	-0.712	-0.980
t-stat	*1.74*	*1.41*	*-2.25*	*-1.93*	*-2.80*	*-4.79*

Panel C. IO Effect and Turnover

	Low	**Turn2**	**Turn3**	**Turn4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.053	0.383	0.354	0.800	0.835	0.781
t-stat	*0.46*	*2.17*	*1.55*	*3.83*	*3.30*	*3.34*
$\boldsymbol{\alpha}_{FF}$	-0.008	0.293	0.228	0.673	0.699	0.706
t-stat	*-0.07*	*2.05*	*1.38*	*4.14*	*3.50*	*3.50*
$\boldsymbol{\alpha}_{ICAPM}$	0.015	0.185	0.019	0.310	0.338	0.323
t-stat	*0.13*	*1.25*	*0.10*	*1.60*	*1.60*	*1.48*
$\boldsymbol{\beta}_{FVIX}$	-0.085	-0.432	-0.733	-1.057	-1.065	-0.981
t-stat	*-0.62*	*-1.88*	*-2.16*	*-3.07*	*-3.08*	*-4.13*

Panel D. IO Effect and Analyst Disagreement

	Low	**Disp2**	**Disp3**	**Disp4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	-0.188	-0.204	-0.142	0.036	0.422	0.610
t-stat	*-1.32*	*-1.52*	*-0.83*	*0.23*	*1.93*	*2.98*
$\boldsymbol{\alpha}_{FF}$	-0.160	-0.161	-0.126	-0.012	0.336	0.496
t-stat	*-1.14*	*-1.24*	*-0.73*	*-0.07*	*1.75*	*2.75*
$\boldsymbol{\alpha}_{ICAPM}$	-0.280	-0.187	-0.193	-0.082	0.080	0.360
t-stat	*-2.00*	*-1.53*	*-1.20*	*-0.52*	*0.38*	*1.70*
$\boldsymbol{\beta}_{FVIX}$	-0.204	0.043	-0.121	-0.236	-0.743	-0.539
t-stat	*-1.09*	*0.34*	*-0.82*	*-1.41*	*-2.49*	*-2.84*

Table 8. Institutional Ownership Effect, Uncertainty, Growth Options, and Earnings Announcements

The table records average returns at earnings announcements of the high-minus-low IO portfolio. EARet refers to raw returns, CAR designates size and book-to-market adjusted returns. The high-minus-low IO portfolio is formed separately in each quintile from the sorts on the variable named in each panel title. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

Panel A. IO Effect and Market-to-Book

	Value	MB2	MB3	MB4	Growth	G-V
EARet	0.504	0.321	0.483	0.421	0.603	0.099
t-stat	*1.03*	*0.80*	*1.70*	*1.89*	*2.75*	*0.24*
CAR	0.392	0.273	0.482	0.299	0.522	0.130
t-stat	*0.93*	*0.76*	*1.66*	*1.21*	*2.47*	*0.38*

Panel B. IO Effect and Idiosyncratic Volatility

	Low	IVol2	IVol3	IVol4	High	H-L
EARet	0.409	0.301	0.189	0.594	0.546	0.137
t-stat	*2.10*	*1.62*	*0.99*	*2.11*	*2.32*	*0.52*
CAR	0.117	0.318	0.260	0.532	0.435	0.317
t-stat	*0.59*	*1.69*	*1.40*	*2.06*	*1.94*	*1.08*

Panel C. IO Effect and Turnover

	Low	Turn2	Turn3	Turn4	High	H-L
EARet	0.569	0.257	0.409	0.147	0.892	0.323
t-stat	*2.18*	*1.56*	*1.77*	*0.51*	*2.96*	*0.88*
CAR	0.415	0.060	0.238	0.109	0.780	0.364
t-stat	*1.65*	*0.38*	*1.13*	*0.46*	*2.65*	*1.03*

Panel D. IO Effect and Analyst Disagreement

	Low	Disp2	Disp3	Disp4	High	H-L
EARet	-0.090	-0.300	1.006	0.351	0.278	0.368
t-stat	*-0.47*	*-0.74*	*2.96*	*1.45*	*1.15*	*1.16*
CAR	-0.275	-0.338	1.098	0.331	0.348	0.623
t-stat	*-1.45*	*-0.88*	*3.26*	*1.71*	*1.62*	*1.90*

Table 9. Anomalies, Institutional Ownership, and Exposure to VIX Changes

Columns one to four report the last slope coefficients from the following four regressions

$$
\begin{aligned}
(2)\qquad Model\ 1: Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta^{CAPM}_{\Delta VIX} \cdot \Delta VIX \\
(3)\qquad Model\ 2: Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta^{CAPM}_{FVIX} \cdot FVIX \\
(4)\qquad Model\ 3: Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta^{FF}_{\Delta VIX} \cdot \Delta VIX \\
(5)\qquad Model\ 4: Ret_t - RF_t &= \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta^{FF}_{FVIX} \cdot FVIX
\end{aligned}
$$

The fifth column is the market beta from the CAPM. Panel A uses, as the left-hand-side variable in the regressions, portfolios that buy/short bottom/top quintile from the sorts on the variable indicated in the leftmost column (for IO, the portfolio switches to buying top and shorting bottom quintile). Panel B uses, as the left-hand-side variable, the difference in returns between arbitrage portfolios from Panel A formed separately in bottom and top IO quintiles. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

	$\beta^{CAPM}_{\Delta VIX}$	β^{CAPM}_{FVIX}	$\beta^{FF}_{\Delta VIX}$	β^{FF}_{FVIX}	β_{MKT}
MB	-0.023	-0.520	-0.008	-0.220	-0.325
t-stat	*-2.85*	*-4.67*	*-2.06*	*-3.63*	*-14.56*
IVol	-0.078	-2.418	-0.030	-1.840	-0.582
t-stat	*-6.22*	*-15.52*	*-2.57*	*-11.49*	*-16.44*
Turn	-0.065	-1.793	-0.038	-1.517	-0.676
t-stat	*-3.89*	*-11.82*	*-2.43*	*-9.15*	*-21.39*
Disp	-0.052	-1.484	-0.022	-1.201	-0.383
t-stat	*-5.51*	*-10.37*	*-2.42*	*-9.36*	*-12.81*
Inst	-0.035	-0.352	-0.024	-0.239	-0.014
t-stat	*-4.39*	*-3.93*	*-4.16*	*-3.42*	*-0.64*

	DVIX1	**FVIX1**	**DVIX3**	**FVIX3**	**Bmkt**
IO-MB	-0.037	-0.452	-0.018	-0.159	-0.003
t-stat	-3.223	-4.810	-1.789	-2.101	-0.123
IO-IVol	-0.019	-1.026	0.002	-0.771	-0.116
t-stat	-1.637	-8.639	0.121	-5.987	-4.880
IO-Turn	-0.031	-0.721	-0.019	-0.623	-0.226
t-stat	-3.150	-6.844	-2.130	-6.303	-8.183
IO-Disp	-0.025	-0.638	-0.021	-0.581	-0.191
t-stat	-1.979	-7.305	-1.916	-6.301	-9.574

Table 10. Anomalies, Volatility Risk, and Investor Sentiment

The table estimates five models and reports only FVIX and sentiment betas from them:

$$\begin{aligned}
(6)\quad Model\ 1: Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta_{FVIX} \cdot FVIX_t \\
(7)\quad Model\ 2: Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta_{Sent} \cdot \Delta Sent_t \\
(8)\quad Model\ 3: Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta_{FVIX} \cdot FVIX_t + \beta_{Sent} \cdot \Delta Sent_t \\
(9)\quad Model\ 4: Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t + \beta_{Sent} \cdot \Delta Sent_t^{\perp} \\
(10)\quad Model\ 5: Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t + \beta_{SMB} \cdot SMB_t \\
&\quad + \beta_{HML} \cdot HML_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{Sent} \cdot \Delta Sent_t^{\perp}
\end{aligned}$$

$Sent_t$ is investor sentiment, and $Sent_t^{\perp}$ is investor sentiment orthogonalized to a number of business cycle variables, which do not include volatility. The arbitrage portfolios that are used on the left-hand side of the regressions above are defined in the heading of Table 9. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2012.

	1	**2**	**3**		**4**	**5**	
	FVIX	$\boldsymbol{\Delta Sent_t}$	**FVIX**	$\boldsymbol{\Delta Sent_t}$	$\boldsymbol{\Delta Sent_t^{\perp}}$	**FVIX**	$\boldsymbol{\Delta Sent_t^{\perp}}$
MB	-0.474	-0.899	-0.380	-0.797	-0.471	-0.397	-0.306
t-stat	*-2.71*	*-3.20*	*-2.35*	*-2.73*	*-1.98*	*-2.37*	*-1.32*
IVol	-0.628	-0.871	-0.589	-0.778	-0.818	-0.535	-0.634
t-stat	*-5.88*	*-4.27*	*-5.61*	*-4.08*	*-5.73*	*-4.18*	*-4.54*
Turn	-0.352	-0.721	-0.325	-0.670	-0.746	-0.262	-0.656
t-stat	*-1.90*	*-2.92*	*-1.70*	*-2.77*	*-4.02*	*-1.25*	*-3.61*
Disp	-0.568	-0.595	-0.548	-0.508	-0.753	-0.487	-0.589
t-stat	*-4.02*	*-2.65*	*-3.71*	*-2.41*	*-4.40*	*-2.98*	*-3.43*
Inst	-0.314	-0.589	-0.314	-0.541	-0.455	-0.289	-0.350
t-stat	*-2.38*	*-2.87*	*-2.22*	*-2.52*	*-2.55*	*-1.91*	*-1.99*

	1	**2**	**3**		**4**	**5**	
	FVIX	$\boldsymbol{\Delta Sent_t}$	**FVIX**	$\boldsymbol{\Delta Sent_t}$	$\boldsymbol{\Delta Sent_t^{\perp}}$	**FVIX**	$\boldsymbol{\Delta Sent_t^{\perp}}$
IO-MB	-0.938	-1.147	-0.874	-0.285	-0.856	-0.953	0.023
t-stat	*-4.19*	*-2.46*	*-3.52*	*-0.76*	*-1.89*	*-4.04*	*0.07*
IO-IVol	-0.636	-0.736	-0.602	-0.640	-0.813	-0.542	-0.626
t-stat	*-3.97*	*-1.89*	*-3.43*	*-1.62*	*-2.44*	*-3.07*	*-1.91*
IO-Turn	-0.611	-0.447	-0.673	-0.340	-0.648	-0.626	-0.434
t-stat	*-3.83*	*-1.13*	*-4.03*	*-0.95*	*-2.47*	*-3.66*	*-1.66*
IO-Disp	-0.443	-0.862	-0.395	-0.798	-0.726	-0.345	-0.614
t-stat	*-2.49*	*-3.62*	*-2.26*	*-3.34*	*-2.89*	*-1.85*	*-2.42*