Robustness Checks for *"Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns"*

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Abstract

This document collects the robustness checks and supplementary tests for the paper "Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns". Section 1 checks robustness of the idiosyncratic volatility discount (brought into question by Fu (2009) and Huang et al. (2010)). Section 2 consider the ability of Conditional CAPM to explain the idiosyncratic volatility discount, the value effect, and their interaction. Section 3 checks the robustness of the results in the paper to using fully tradable versions of FVIX and FIVol that use expanding window factor-mimicking regression, as well as other modifications of FVIX factor. Section 3 also considers the alternative volatility risk factors of Adrian and Rosenberg (2008) and Chen and Petkova (2012) and their relation to the volatility risk factors we use. Adrian-Rosenberg volatility factors are then used to expand the sample period to 1963-2017, beyond the period of VIX availability (1986-2017). Section 4 looks at the overlap between FVIX and RMW and the overlap between FVIX and FMAX and conclude that RMW and FMAX are imperfect proxies for FVIX. Section 4 also looks at relation between FVIX, FIVol, and various liquidity risk factors and funding liquidity measures, as well as relation between FVIX, FIVol and mispricing factors from Stambaugh and Yuan (2017). Section 5 collects miscellaneous robustness checks.

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1 On the Robustness of the Idiosyncratic Volatility Discount

1.1 Revisiting Bali and Cakici (2008)

In a recent paper, Bali and Cakici (2008) claim that the idiosyncratic volatility discount is not robust to reasonable changes in the research design. In particular, they argue that measuring idiosyncratic volatility using monthly returns or looking at NYSE only firms eliminates the idiosyncratic volatility discount.

When we try to mimic the results in Bali and Cakici (2008), we find that their results are contaminated by selection bias. When Bali and Cakici look at NYSE only firms, they define a NYSE firm using the current listing reported in the `hexcd` listing indicator from the CRSP returns file. That creates a strong selection bias, because only good performers remain NYSE firms from the portfolio formation date till now. Bad performers, even if they were NYSE firms at the portfolio formation date, are likely to be subsequently downgraded to OTC markets or regional stock exchanges, and therefore they do not make it into the Bali and Cakici "NYSE only" sample. On the other hand, good performers, even if they were NASDAQ at the portfolio formation date, are likely to make it into the "NYSE only" sample, because they may have been upgraded to NYSE since then. This positive bias in returns is evidently stronger for high idiosyncratic volatility firms, which are more likely to have extremely good performance (and be incorrectly included in the sample) or extremely bad performance (and be incorrectly excluded from the sample).

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

We follow Bali and Cakici (2008) in measuring idiosyncratic volatility from monthly data. We define it as the standard deviation of the Fama-French model residuals, where the Fama-French model is fitted to monthly returns from the past 60 months (at least 24 valid observations are required for estimation). The monthly idiosyncratic volatility portfolios are rebalanced at the end of each month and held for one month afterwards. The daily idiosyncratic volatility measure in Bali and Cakici (2008) is the same as the one we use throughout the paper.

In Table 1A we look at the idiosyncratic volatility discount in the NYSE only sample. Panel A looks at the portfolios formed using the volatility of daily returns in the past month, and Panel B looks at the portfolios formed using the volatility of monthly returns in the past 24 to 60 months. In the first two rows, we mimic Bali and Cakici (2008) by using `hexcd` from the CRSP returns file to classify firms as NYSE.

The raw returns are within 1 bp per month of what Bali and Cakici (2008) show in their Table 1, Panel B, and in their Table 3, Panel B. It convinces us that they were using the `hexcd` listing indicator, even though they are not explicit about it.

When we matched Bali and Cakici (2008) in the top row of Table 1A, we ignored delisting returns as Bali and Cakici apparently did. Adding the delisting returns back increases the idiosyncratic volatility discount by 3 bp per month, as shown in the third row.

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

Overall, Table 1A demonstrates that Bali and Cakici (2008) fail to find the idiosyncratic volatility discount because of the pitfalls in their research design. Once we eliminate the selection bias that contaminates their results, we find the idiosyncratic volatility discount alive and well exactly for the sample where Bali and Cakici claimed to find the greatest evidence against it.

1.2 The Idiosyncratic Volatility Discount and the Short-Term Return Reversal

Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) show that the idiosyncratic volatility discount is related to the short-term return reversal driven by microstructure imperfections. The short-term return reversal refers to the negative autocorrelation in the monthly returns to the least liquid stocks first documented in Jegadeesh (1990). This reversal is a microstructure phenomenon with the life of only one to two months.

However, both Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) offer only indirect evidence that the idiosyncratic volatility discount is caused by the short-term return reversal. Fu (2009) shows that in the portfolio formation month high volatility firms earn, on average, extremely high returns, and low volatility firms earn low returns (the idiosyncratic volatility discount means that the reverse is true in the holding period). Huang, Liu, Rhee, and Zhang (2010) use a factor long in winners and short in losers during the portfolio formation month and show that adding this factor to the Fama-French model explains the idiosyncratic volatility discount.

In this subsection, we perform a simple and direct test of whether the idiosyncratic volatility discount is subsumed by the short-term reversal. In Table 2A, we look at the performance of the arbitrage portfolio long in low and short in high idiosyncratic volatility firms in each of the twelve months after the portfolio formation (the rest of the paper considers the returns to this portfolio only in the first month). If the idiosyncratic volatility discount is caused by the short-term return reversal, we expect the idiosyncratic volatility discount to be dramatically weaker starting with the second or the third month after the portfolio formation date.

Table 2A shows that this is not the case. Whether we look at the CAPM alpha or the Fama-French alpha, the full sample period or start in 1986, when VIX becomes available, the idiosyncratic volatility discount does indeed drop by about a third between the first month and the second month, from about 70 bp per month to about 45 bp per month, but it remains economically large and statistically significant. Over the year after portfolio formation the idiosyncratic volatility discount decreases by almost a half, but even in the twelfth month after the portfolio formation it is about 35 bp per month and statistically significant (sometimes marginally so). The relatively long life of the idiosyncratic volatility discount is clearly inconsistent with the short-term return reversal causing the idiosyncratic volatility discount, though the drop in the idiosyncratic volatility discount between the first and the second month shows that the short-term return reversal does play a role. However, this role is limited to at most a third of the idiosyncratic volatility discount.

Table 2A also reports the FVIX betas from the two-factor model with the market factor and FVIX. If all changes in the idiosyncratic volatility discount are caused by changes in aggregate volatility risk and the fact that the link between idiosyncratic volatility and aggregate volatility risk becomes weaker as idiosyncratic volatility gets more stale, we expect the FVIX betas to mimic the pattern in the alphas. If the drop in the idiosyncratic volatility discount between the first and the second months is caused by the short-term return reversal effect, we do not expect to see any drop in the FVIX betas around this time.

In Table 2A we observe that the FVIX betas are flat across the time period, decreasing only slightly for the portfolios formed using idiosyncratic volatility from 9 to 12 months ago. The FVIX betas in all periods are large and highly significant. There is a slight increase instead of a decrease in the FVIX betas between the first and the second month, meaning that the weakening of the idiosyncratic volatility discount by a third around this date is indeed for the microstructure reasons mentioned in Fu (2009) and Huang, Liu, Rhee, and Zhang (2009) and suggesting that the FVIX factor and the short term reversal have nothing in common.

To sum up, this section shows that the short term reversal is responsible for at most one third of the idiosyncratic volatility discount, while the other two thirds remain significant for a year or longer and require the use of FVIX as the explanation. We also find that the short term reversal and the aggregate volatility risk explanation of the idiosyncratic volatility discount do not overlap.

1.3 Descriptive Statistics of Sorts on Idiosyncratic Volatility and Market-to-Book

Table 4A shows that a large part of both the value effect and idiosyncratic volatility discount, as well as a large part of their relation to idiosyncratic volatility and market-to-book, respectively, comes from the large negative beta of the high volatility growth portfolio (the intersection of the top idiosyncratic volatility quintile and top market-to-book quintile, denoted IVol55 in Table 5A).

Panel A of Table 3A tabulates median size across five-by-five sorts on idiosyncratic volatility and market-to-book. Ang et al. (2006) show that in cross-section idiosyncratic volatility is negatively related to size; Fama and French (1995) find a positive cross-sectional relation between market-to-book and size. Panel A of Table 3A confirms both findings: firms in the top idiosyncratic volatility quintile are an order of magnitude smaller than those in the bottom idiosyncratic volatility quintile, and firms in the top market-to-book quintile (growth firms) are several times larger than those in bottom market-to-book quintile (value firms). Consequently, firms in the high volatility growth portfolio are the largest among firms in the top idiosyncratic volatility quintile, and their size is comparable to that of value firms in the middle idiosyncratic volatility quintile.

Panels B-D of Table 3A find similar size-related patterns in median stock price, median price impact (estimated by the Amihud, 2002, measure) and median effective bid-ask spread (estimated by the Roll, 1984, measure). Growth firms, being larger, have roughly twice higher stock prices and several times lower price impact than value firms, while bid-ask spread for growth firms is close to that of value firms. High volatility firms have three to four times lower stock price that low volatility firms, price impact that is larger by an order of magnitude, and bid-ask spread that is twice or thrice larger than that of low volatility firms. Firms in the high volatility growth portfolio hence have intermediate values of stock price, price impact, and bid-ask spread, suggesting that trading those firms, which create a large part of both the value effect and the idiosyncratic volatility discount, is not likely to be prohibitively costly.

Panels E and F tabulate average returns in the month before portfolio formation and in the eleven months preceding that month across the same five-by-five sorts on idiosyncratic volatility and market-to-book. Firms in the high volatility growth portfolio (IVol55 in the paper) seem to be winner firms, which should work against them having negative alphas, but their return in the portfolio formation month is not particularly high, meaning that they are the least likely of all high volatility firms to suffer from the short-term reversal.

Overall, Table 3A suggests that the value effect and the idiosyncratic volatility discount is unlikely to be driven by extremely illiquid firms, which is consistent with the evidence in Panel B of Table 3A that dropping low-price, small, illiquid firms from the sample does not significantly affect the idiosyncratic volatility discount or its aggregate volatility risk explanation.

Panels G and H of Table 3A presents median values of several distress measures across five-by-five double sorts on idiosyncratic volatility and price-to-cash-flow ratio. Panel G looks at leverage and finds no difference in leverage between high and low volatility firms, but a significant difference in leverage between value and growth firms: value firms are about six to seven times as levered as growth firms. This difference goes against the hypothesis growth firms can be option-like for reasons other than their growth options: if one thinks of their equity as a call option on the assets, this option is apparently deeply in the money.

Panel H looks at median O-score, which captures probability of distress. Again, value firms seem more distressed than growth firms, but now high IVol firms are also more distressed than low IVol firms. The difference in O-score between the highest and lowest IVol quintile is, however, relatively small - if we compare it to sorts on O-score, this difference would be the difference between the second and third quintile. We also do not observe that either the spread in O-score between high and low IVol firms is wider for growth firms than for value firms nor that high IVol growth firms are the most distressed ones, suggesting that our results are unlikely to be driven by option-likeness coming from distress rather than growth options.

2 Idiosyncratic Volatility Discount, the Value Effect, and the Conditional CAPM

2.1 Using Market-to-Book as a Growth Options Measure

Earlier versions of the paper used market-to-book as a measure of growth options. Compared to other popular valuation ratios (price-to-earnings, price-to-cash-flow), market-to-book allows studying a larger cross-section: in analysis based on P/E ratio, stocks with negative earnings are traditionally discarded, but these stocks are kept in a similar analysis based on market-to-book, as even negative earnings stocks have positive book value of equity.

We have switched to using price-to-cash-flow ratio in the paper instead of market-to-book to make our empirical tests as close as possible to our model predictions, but in this subsection we reproduce old results with market-to-book and use them in the rest of this document. As one can see from comparing Tables 3 and 4 in the paper and Tables 5A and 6A to be discussed in this section, the results are very close; the same is true for all other results in this document - replacing market-to-book with price-to-cash-flow ratio would not change them much.

In Panel A of Table 4A, we look at value-weighted CAPM alphas in the five-by-five independent portfolio sorts on market-to-book and IVol.[1] Going across rows and confirming Figure 1B in the paper, we observe that he magnitude of the IVol discount monotonically increases from 20 bp per month, t-statistic 0.51, in the extreme value quintile to 96.5 bp per month, t-statistic 3.28, in the extreme growth quintile. The difference is statistically significant with t-statistic 2.20. Going down the columns of Panel A, we also observe that the value effect starts with almost exactly zero CAPM alpha in the lowest IVol quintile and ends up with the CAPM alpha of 77 bp per month, t-statistic 2.14, in the highest IVol quintile. The results in Panel A of Table 3 in the paper (with price-to-cash-flow instead of market-to-book) are very similar: for example, the value effect in the top IVol quintile is 83 bp per month, t-statistic 2.16. The only visible difference is that the paper reports somewhat weaker IVol discount in the middle price-to-cash-flow quintiles.

Panel B of Table 4A suggests that there is no IVol discount and no value effect after we control for volatility risk. The IVol discount turns insignificantly negative in all market-to-book quintiles and no longer depends on market-to-book. The value effect in alphas from the three-factor volatility model fluctuates between -22 bp per month and 5 bp per month, but is never statistically significant and does not depend on IVol. Panel B in Table 3 in the paper reports very similar results with a few random (marginally) significant alphas in the middle of the panel. For example, Panel B of Table 4A reports the alpha of the value-minus-growth portfolio in the top IVol quintile at -10 bp per month after FVIX and FIVol are controlled for; Panel B in Table 3 in the paper reports similar alpha at 0.2 bp per month.

Panel C of Table 4A shows that the FVIX betas are closely aligned with the CAPM alphas in Panel A. FVIX beta of the low-minus-high IVol portfolio (rightmost column) is always negative and strongly and monotonically increases in absolute magnitude with market-to-book, and the FVIX beta of the value-minus-growth portfolio (bottom row) similarly increases with IVol. Comparing the FVIX betas of the low-minus-high IVol portfolios and the value-minus-growth portfolios, we find that FVIX is more likely to help in explaining the IVol discount than the value effect. The FVIX beta of the value-minus-growth portfolio is only significantly negative in the highest IVol quintile, the quintile in which the value effect is by far the strongest.

[1] The sorts are performed using NYSE (`exchcd`=1) breakpoints. The results are robust to using conditional sorting and/or CRSP breakpoints, as well as to using raw returns or the Fama-French alphas instead, and/or using equal-weighted returns, see Section 5.5 of this document for the latter.

In Panel C in Table 3 in the paper, FVIX betas of low-minus-high IVol portfolios are uniformly lower by roughly 15%, but FVIX betas of the value-minus-growth portfolio are higher and remain significant even in the third and fourth IVol quintiles.

Panel D of Table 4A reports the FIVol betas and finds that FIVol is the factor that explains the value effect, most particularly the positive alphas of value stocks (the FIVol betas of these stocks are large and negative), but contributes little to explaining the IVol discount. We also find that the FIVol betas of the value-minus-growth portfolio are equally strong in all IVol quintiles.[2].

In Panel D in Table 3 in the paper, FIVol betas of value-minus-growth portfolios are somewhat smaller (in the top IVol quintile, Panel D in Table 3 in the paper reports FIVol beta of -0.280 vs. -0.397 in Panel D of Table 4A), and the positive FIVol betas of low-minus-high IVol portfolios are statistically significant.

Overall, the impression from comparing Table 3 in the paper and Table 4A is that in the double sorts on market-to-book and IVol (which capture a broader cross-section), the three-factor volatility model explains the value effect, the IVol discount, and their interaction slightly better than in the double sorts on price-to-cash-flow ratio and IVol. FVIX is better at explaining the value effect from price-to-cash-flow sorts, and FIVol is slightly worse at doing that. FIVol is also less helpful in explaining the IVol discount in the subsample with positive price-to-cash-flow ratio (i.e., the sample in Table 3 in the paper).

Table 5A performs the analysis similar to Table 4 in the paper, but using price-to-cash-flow ratio instead of market-to-book. In Table 5A, HML is the Fama and French (1993) HML factor and takes place of VMG in Table 4 in the paper. IVol55 in Table 5A is analogous to HiVolG in Table 4 in the paper and represents high IVol growth firms (from the intersection of the top IVol quintile and the top market-to-book quintile). HMLh, IVol, and IVolh are defined similarly to VMGh, IVol, and IVolh (IVol is the exact same portfolio in both tables).

Comparison between Table 5A and Table 4 in the paper confirms what we learned from comparison of Table 4A and Table 3 in the paper. First, FVIX is more helpful in explaining the value effect from price-to-cash-flow sorts than from market-to-book sorts. For example, Table 5A reports FVIX beta of HML at -0.43, t-statistic -1.85, compared

[2] In equal-weighted returns in Section 5.5 in this document, we do see significantly more negative FIVol betas of the value-minus-growth portfolio in the high IVol quintile

to FVIX beta of value-weighted VMG at -0.61, t-statistic -4.19, in the paper. Second, in Table 4 in the paper the value effect is significant, although only in equal-weighted returns: in Table 5A, the CAPM alpha of HML is 31 bp per month, t-statistic 1.56, in the 1986-2017; Table 4 in the paper reports the CAPM alpha of VMG at 32.7 bp per month, t-statistic 1.45 (value-weighted) and at 70.3 bp per month, t-statistic 3.12 (equal-weighted). (FVIX and FIVol do explain the equal-weighted alpha of VMG, reducing it to 11.7 bp per month). Third, in Table 5A FIVol is somewhat more of a hindrance in explaining the IVol effect in value-weighted (but not equal-weighted returns): FIVol betas of the IVol and IVolh portfolios have the wrong (positive) sign, but are numerically small and statistically insignificant.

2.2 Conditional CAPM Results

Barinov (2008) develops a comparative statics model similar to Johnson (2004) replaced disagreement with idiosyncratic volatility and leverage (the source of convexity in the Johnson model) with by growth options, and applies the Johnson (2004) result that the beta of an option declines in idiosyncratic volatility of the underlying volatility, because option value elasticity with respect to the value of the underlying asset also declines in idiosyncratic volatility.

Barinov (2008) also shows that growth options and idiosyncratic volatility interact to create the conditional CAPM effects, i.e., growth firms with the highest idiosyncratic volatility have the most pro-cyclical betas. Thus, the beta of value-minus-growth strategy will be the most counter-cyclical in the high idiosyncratic volatility subsample and the beta of high-minus-low idiosyncratic volatility strategy will be the most counter-cyclical in the growth subsample.

Babenko et al. (2016) develop a similar prediction in a model in which the firm value is additive in systematic and idiosyncratic shocks. If the part of the firm that is exposed to idiosyncratic shocks grows in size (relative to the rest of the firm), the impact of systematic shocks on the firm value and hence the firm beta decreases, while idiosyncratic volatility increases. Babenko et al. also assume that growth options are more sensitive to idiosyncratic shocks than assets in place and thus their model generates the value effect that should be explained by making the beta time-varying using the standard conditional CAPM setup. Similarly, Babenko et al. predict that conditional CAPM should explain the idiosyncratic volatility discount, and also predict the existence of the link between the value effect and idiosyncratic volatility.

Chen et al. (2020) suggest yet another mechanism that would make the market beta of high idiosyncratic volatility firms procyclical: they focus on risk-shifting in distressed firms, which tend to invest in high-volatility projects counting on the downside protection shareholders get from limited liability. The potential of this risk-shifting from shareholders onto bondholders is obviously greater in bad times, when firms are more likely to be distressed and volatile, and the magnitude of risk-shifting is greater for high volatility firms that have many high volatility projects to choose from. Thus, Chen et al. (2020) argue, high idiosyncratic volatility firms are low-risk because such firms have procyclical market betas (lower in recessions). Another prediction from Chen et al. (2020), which would be at odds with Babenko et al. and the evidence we present in Table 4A, would be that the idiosyncratic volatility discount should be stronger for distressed firms, which are much more likely to be value, not growth firms.

In Tables 3A and 4A, we use the long-short portfolios from Table 5A to test the performance of conditional CAPM. The long-short portfolios are HML (the Fama-French value-minus-growth factor), IVol (long in the lowest IVol quintile and short in the highest IVol quintile) and three more portfolios from five-by-five sorts on IVol and market-to-book (see Table 4A for full sorts). IVolh is long in lowest IVol growth portfolio and short in highest IVol growth portfolio. HMLh is long in highest IVol value and short in highest IVol growth portfolio. IVol55 is long in high IVol growth portfolio and short in one-month Treasury bill.

We expect that the market betas of the HML, HMLh, IVol, and IVolh portfolios will increase in recessions, and the market beta of the IVol55 portfolio will decrease in recessions. We also add four more portfolios to check whether the conditional CAPM can explain the relation between the value effect (the idiosyncratic volatility discount) and limits to arbitrage. IVol IO (IVol Sh) is the portfolio long in the lowest volatility quintile and short in the highest volatility quintile formed within the lowest institutional ownership (the highest probability to be on special) subsample. HML IO and HML Sh repeat the same using market-to-book instead of idiosyncratic volatility. We predict that the betas of these four portfolios increase in recession.

Our model predicts that high volatility firms and growth firms outperform the CAPM prediction when aggregate volatility increases. The decrease in the market beta of these firms during recessions (when volatility is typically high) is consistent with this prediction, since lower beta in recession implies a smaller increase in the cost of capital and a smaller decrease in the firm value. Yet, while the explanations of the value effect and the idiosyncratic volatility discount in our paper and in Babenko et al. are not mutually exclusive, it is interesting to gauge their relative importance.

In Table 6A, we look at the average market betas across the states of the world for the nine arbitrage portfolios we study. Similar to Petkova and Zhang (2005), we assume that the expected market risk premium and the conditional beta are linear functions of the four commonly used business cycle variables - the dividend yield, the default spread, the one-month Treasury bill rate, and the term spread. We define the bad state of the world, or recession, as the months when the expected market risk premium is higher than its in-sample mean. The expected market return is estimated as the fitted part of the regression

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

Since the data on the four business cycle variables are available for a long period of time, the sample period in Table 6A is from August 1963 to December 2017, based on the availability of daily returns on CRSP (daily returns are necessary to compute idiosyncratic volatility).

To estimate the conditional CAPM beta, we run the regression

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

and define the conditional beta as

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

The left part of Table 6A looks at value-weighted returns and shows strong evidence consistent with our view of the value effect and idiosyncratic volatility discount as risk-based effects caused by the interaction of growth options and idiosyncratic volatility. For value-weighted returns, we find that for the IVol and IVolh the conditional CAPM betas are by 0.260 and 0.386 higher in recessions than in expansions, t-statistics 6.57 and 10.6, respectively. It means that exploiting the idiosyncratic volatility discount implies large increases in risk exposure during the high-risk periods. Also, the IVol55 portfolio turns out to be a good hedge against adverse business cycle movements, as its beta is by 0.298, t-statistic 12.9, lower in recessions than in expansions. The right part of Table 6A, which uses equal-weighted returns, shows very similar results.

We also find that the CAPM beta of the HML factor increases in recessions by 0.267, t-statistic 10.1. The CAPM beta of HMLh portfolio shows an even stronger increase by 0.398, t-statistic 8.37, for value-weighted returns and by 0.391, t-statistic 9.25, for equal-weighted returns. The difference in the conditional beta sensitivity to business cycle between HML and HMLh reinforces our conclusion that the value effect is at least partly driven by the interaction of growth options and volatility.

Interestingly enough, the IVol and HML portfolios formed in the highest limits-to-arbitrage subsamples demonstrate the widest spread in the betas between expansion and recession. In recession, the CAPM beta of the value-weighted IVol IO portfolio increases by 0.387, t-statistic 5.14, and the CAPM beta of the value-weighted IVol Sh portfolio increases by 0.625, t-statistic 5.79, which are about 1.5 to 2.4 times greater than the average change in the beta of the IVol portfolio from expansion to recession. Similarly, the beta of the value-weighted HML IO portfolio increases in recessions by 0.455, t-statistic 7.87, and the beta of the value-weighted HML Sh portfolio increases in recessions by 0.734, t-statistic 10.1. The results in equal-weighted returns are similar.

Overall, the conditional CAPM results are consistent both with Barinov (2008) and Babenko et al. (2016), as well as our paper, since the conditional CAPM suggests that exploiting the value effect and the idiosyncratic volatility discount exposes the investor to increased risk (and, consequentially, to lower returns) during hard times.

Table 7A runs the horse race between the conditional CAPM and the volatility factor model with FVIX and FIVol from the paper. The first five columns largely reproduce the volatility factor model results and conditional CAPM results from the paper, which will serve as the benchmark for the horse race. Comparing the conditional CAPM with the volatility factor model, we find that making the market beta conditional reduces the alphas of the nine anomalous portfolios by an average of 19 bp per month and does not change their statistical significance, while adding FVIX and FIVol reduces the alphas by an average of 80 bp per month and makes all of them insignificant.

The last three columns perform the direct horse race between the conditional CAPM and the volatility factor model by adding FVIX and FIVol into the conditional CAPM: the market beta remains conditional, but the FVIX and FIVol betas are assumed to be constant. The first thing we notice is that the "conditional volatility factor model" alpha is within a few bps of the volatility factor model alpha, that is, once FVIX and FIVol are controlled for, making the market beta conditional does not add anything to the model's ability to explain the alphas of the nine anomalous portfolios. Second, we notice that FVIX beta is unaffected by making the market beta conditional, while FIVol beta becomes less negative, but stays significant (the average reduction for the cases when FIVol beta starts significant in the volatility factor model is 28%).

We conclude that it is more likely that the ability of the conditional CAPM to partly explain the anomalies we study is coming from its overlap with one of our factors (FIVol) than the other way around.

3 Alternative Measures of Volatility Risk

3.1 Tradable FVIX and FIVol: Is There a Look-Ahead Bias?

3.1.1 Tradable FVIX

The main difference between our results and those of Ang et al. (2006) comes from the fact that Ang et al. perform the factor-mimicking regression separately for each month, thus estimating six parameters (the constant and the five slopes on the five base assets, which are quintile portfolios pre-sorted on past sensitivity to VIX changes) using roughly 22 daily returns. Such estimates are obviously imprecise, and of particular concern is the noise in the constant, since the factor-mimicking portfolio, FVIX, is defined as the fitted part of the regression minus the constant, so the constant impacts greatly the estimate of the FVIX risk premium.

In our paper, we perform one factor-mimicking regression for the full sample, which increases the number of observations and precision of our estimates quite drastically. This is a common thing to do since the classic paper by Breeden, Gibbons, and Litzenberger (1989). The benefit of using the single regression is that doing so significantly improves the precision of the estimates. The potential drawback is that the results may suffer from the look-ahead bias. Indeed, in 1986 investors could not run the factor-mimicking regression of the daily VIX changes on returns to base assets using the data from 1986 to 2017. The common defense here is that in 1986 investors are very likely to be much more informed about how to mimic changes in expected aggregate volatility than the econometrician. Allegedly, long before the VIX index became available, investors had an idea about what current expected aggregate volatility and its change were. Hence, by 1986 they probably had years and even decades of experience of mimicking innovations to expected aggregate volatility (unobservable to the econometrician before 1986). Assuming that the weights in the FVIX portfolio are stable through time, it is possible that in 1986 investors already knew the weights that the econometrician was able to figure out only by the end of 2017.

In this subsection we revisit all results in the paper making the conservative assumption that the information set of investors is the same as the information set of the econometrician. We perform the factor-mimicking regression of daily change in VIX on excess returns to the base assets using only the past available information. That is, if we need the weights of the base assets in the FVIX portfolio in January 1996, we perform the regression using the data from January 1986 to December 1995. We then multiply the returns to the base assets in January 1996 by the coefficients from this regression to get the FVIX return in January 1996. Then in February 1996 we run a new regression using the data from January 1986 to January 1996, etc. The resulting version of FVIX is a tradable portfolio immune from the look-ahead bias. We call this portfolio FVIXT.

Table 8A presents the correlation matrix for our FVIX, its fully tradable version FVIXT, and the Ang et al. (2006) original version of FVIX (FVIXO) in 1986-2017, a much longer sample than 1986-2000 in Ang et al. (2006). FVIX and FVIXT have 0.99 correlation, and their correlations with the change in VIX, the variable they mimic, are very close at 0.731 and 0.738. FVIXO seems to be significantly noisier because of the estimation error in the short estimation window: its correlation with the change in VIX is 0.607, and its correlation with our baseline FVIX stands at 0.768 (so if we assume our FVIX is pure signal, roughly 40% of FVIXO variation, $1 - 0.768^2$, is noise).

Panels D and E look at alphas and betas of FVIXT and FVIXO, respectively. The alphas and betas come from the CAPM, three-factor Fama and French (1993) model and Carhart (1997) model. While the average returns of FVIXT and FVIXO look relatively close, the alphas of FVIXT are almost the same as the alphas of FVIX and are similarly highly significant (the paper reports the CAPM/FF alphas of FVIX at -46 bp and -44 bp per month, with t-statistics of -4.73 and 4.00), but the alphas of FVIXO are 20 bp per month smaller and statistically insignificant. On the one hand, the difference between alphas of FVIXT and FVIXO is similar to the difference in their raw returns; on the other hand, the standard error of the alphas, implied by the t-statistics, is three times larger for FVIXO alphas, indicating again that FVIXO is rather noisy.

Panel C of Table 8A looks at the Sharpe ratios and appraisal ratios of the standard asset-pricing factors (market, SMB, HML, Mom), as well as the alternative versions of FVIX. Column one of Panel C reports the average returns of all factors and finds that the average return of all FVIX versions is similar and the absolute magnitude of the said return significantly exceeds that of the average returns to other factors.

However, the standard deviations of FVIX returns (column two) are also significantly larger than those of standard asset-pricing factors, and therefore in column three the Sharpe ratios of FVIX versions (0.229 for baseline FVIX, 0.132 for FVIXO) are not that far from, e.g., the Sharpe ratio of the momentum factor (0.157).

It is also interesting to compare standard deviations of FVIX versions. FVIXT predictably has the lowest standard deviation (4.52% vs. 5.98% for the baseline FVIX), as FVIXT loses the outlier of October 1987 to the learning sample (the outlier is included in the factor-mimicking regression, but FVIXT itself starts in 1990). FVIXO has the highest standard deviation at 7.09%, consistent with our view that this version of FVIX (used in Ang et al., 2006) has a significant amount of noise in it due to the short estimation window.

Column four shows that the high average returns of FVIX versions are coming primarily from the fact that the FVIX factor shorts stocks aggressively in order to produce positive returns when VIX increases and thus the FVIX factor has a very negative market beta, as reported in Panel D. The CAPM alphas of FVIX versions are close to the CAPM alpha of HML and below the CAPM alpha of Mom. The appraisal ratios (column five) of FVIX and FVIXT are significantly larger than those of HML and Mom, but the appraisal ratio of FVIXO is almost an order of magnitude smaller than that of FVIX and FVIXT, once again confirming that the Ang et al. version of FVIX (which we call FVIXO) is very noisy.

3.1.2 Tradable FIVol

When it comes to forming a fully tradable version of FIVol, we have two instances in which future information is used. First, $\overline{IVOL}^U$, the variable FIVol mimics, is the residual from full-sample ARMA(1,1) fitted to $\overline{IVOL}$, average idiosyncratic volatility of all stocks in the market. Again, investors probably have more experience than the econometrician in forecasting average idiosyncratic volatility. Second, our factor-mimicking regression that we use to form FIVol is also a full-sample one.

Therefore, we form two versions of tradable FIVol. The first one, FIVolT, uses an expanding window factor-mimicking regression, similar to the one we use to form FVIXT, but the variable being mimicked is still $\overline{IVOL}^U$, the shock to average idiosyncratic volatility from the full-sample ARMA(1,1). However, with $\overline{IVOL}$ being available starting in 1963, we can afford a longer learning sample, 1963-1985, and then the expanding window and the out-of-sample use of factor-mimicking regression coefficients starts.

The second version of tradable FIVol, dubbed FIVolTT, goes further and also uses expanding window and out-of-sample forecast to form the innovation to $\overline{IVOL}$, which we denote $\overline{IVOL}_T^U$. We use the first ten years of our sample (1963-1972) as the learning sample for the ARMA(1,1) model fitted to $\overline{IVOL}$ and then make an out-of-sample forecast of $\overline{IVOL}$ for January 1973. The difference between this forecast and $\overline{IVOL}$ yields the January 1973 value of $\overline{IVOL}_T^U$. Then we expand the sample we use to estimate the ARMA(1,1) model for $\overline{IVOL}$ by one month (i.e., we include January 1973 in this sample), form an out-of-sample forecast of $\overline{IVOL}$ for February 1973, use it to compute the February 1973 value of $\overline{IVOL}_T^U$, etc.

Once the $\overline{IVOL}_T^U$ series is ready, we use 1973-1985 as the learning sample for the factor-mimicking regression and similarly expand it one month at a time (the base assets for the factor-mimicking regression, which are the quintile portfolios sorted on sensitivity to innovations to $\overline{IVOL}$ in the past 60 months, are also now formed using $\overline{IVOL}_T^U$ as this innovation rather than $\overline{IVOL}^U$).

Panel B of Table 8A reports the correlations between the two innovations to average idiosyncratic volatility, $\overline{IVOL}^U$ and $\overline{IVOL}_T^U$, and the three versions of FIVol. The correlation between $\overline{IVOL}^U$ and $\overline{IVOL}_T^U$ is 0.998, suggesting that there is little difference between the innovations from the full-sample and expanding-window ARMA(1,1). The correlations of FIVol with its two alternative versions, FIVolT and FIVolTT, are lower, but still very high at 0.927 and 0.938, respectively.

The descriptive stats of the three versions of FIVol are in Panel C of Table 8A. FIVolT has the smallest average return and CAPM alpha (-1.55% and -0.97% per month, respectively, as compared to -1.94% and -1.22% for FIVol). FIVolTT has the largest average return and CAPM alpha, but its standard deviation is also much higher (due to the extra noise from the two expanding-window regressions), and thus the Sharpe ratio and the appraisal ratio of FIVolTT are the smallest.

Panels F and G of Table 8A present alphas and betas of FIVolT and FIVolTT from standard asset-pricing models, which come out similar to what is reported in Panel C of Table 1 in the paper for the original FIVol factor. Both FIVolT and FIVolTT load negatively on MKT, SMB, and HML, positively on momentum, and insignificantly on CMA and RMW. The negative loading on HML confirms one of the main results in the paper that FIVol and HML strongly overlap, and indeed, in Panels F and G of Table 8A controlling for HML produces the smallest alphas of FIVolT and FIVolTT (which come from the three-factor and five-factor Fama-French models).

3.1.3 Using Tradable FVIX and FIVol to Explain the Anomalies

Table 9A uses the three alternative versions of FVIX to explain the IVol discount and the value effect. Panel A fits the two-factor model with the market factor and different versions of FVIX to the long-short portfolios from Table 5A, in order to observe the clean effect of changes in the factor-mimicking procedure. We observe that FVIX and FVIXT betas are usually close, with the alphas from two-factor model with FVIXT being a bit larger than the alphas from the two-factor model with FVIX. The two-factor model with FVIXO, however, produces numerically small and statistically insignificant FVIXO betas and large and significant alphas, consistent with the evidence above that FVIXO is a very noisy version of FVIX.

Panel B of Table 9A repeats the analysis in Panel A using our preferred model, the volatility factor model with FVIX and FIVol, instead of the two-factor model in Panel A. As in Panel A, Panel B replaces FVIX with FVIXT and then with FVIXO. The results are qualitatively very similar to Panel A: FVIX and FVIXT betas of the long-short portfolios capturing the IVol discount and the value effect are similar, the volatility factor model with FVIXT produces somewhat larger, though still insignificant alphas. However, FVIXO betas are numerically small, statistically insignificant, and the volatility factor model with FVIXO fails to explain the IVol discount. The latter conclusion is similar to the one Ang et al. draw in their paper using conditional sorts (on FVIXO beta and then on IVol), and our analysis reveals that failure of FVIXO to explain the IVol discount is due to FVIXO being noisy because of imperfect factor-mimicking procedure that estimates the factor-mimicking regression separately for each month, effectively estimating 6 parameters in samples of about 22 observations.

Panel C of Table 9A compares three alternative versions of the volatility factor model: the baseline one with FVIX and FIVol (also presented in Table 5A), the one with FVIXT and FIVolT, and the one with FVIXT and FIVolTT. We observe that all three models produce very similar alphas that are within 10 bp per month of each other. The only exception is the alpha of IVolh portfolio, which is visibly higher (but still insignificant) when either FIVolT or FIVolTT are used in the volatility factor model, but this increase compared to the baseline model comes from positive rather than negative FIVol betas of IVolh.

We conclude that the results in the paper are not contaminated by the potential look-ahead bias in either FVIX or FIVol. We can achieve very similar results using the fully tradable versions of FVIX and FIVol that uses only the information available to the econometrician in each moment of time. We prefer the full-sample version of FVIX because it is less noisy in the early years of the sample and using it allows us to keep five more years of data (1986-1990) that we have to forego to the learning sample if we have to use the tradable version of FVIX. For consistency, in the main text of the paper we also use FIVol, though the results would be similar with FIVolT or FIVolTT.

3.2 Long-Run and Short-Run Volatility Risk Factors

Several recent papers have suggested alternative ways of measuring volatility risk. While simple estimates of innovations to market volatility appear not to be priced, Adrian and Rosenberg (2008) suggest estimating a Component GARCH (C-GARCH) model for market volatility. C-GARCH model assumes that market volatility has two components, the short-run one, the shocks to which quickly die out, and the long-run one, with extremely persistent shocks. Adrian and Rosenberg (2008) show that both components of market volatility are priced and the volatility factor model with the market factor and the two volatility innovations has better fit than alternative asset-pricing models.

The split of market volatility into short-run and long-run component is interesting, because it can potentially shed light on the relation between our work, on the one hand,

and the theoretical paper of McQuade (2018) and the work of Campbell et al. (2018), on the other hand. McQuade (2018) solves his model using asymptotic expansions, and this technical method requires the assumption that it is long-run shocks to volatility that explain the low expected returns to distressed firms. Hence, the empirical prediction of McQuade (2018) is that the value effect should be explained by the factor that mimics innovations to long-run volatility. Campbell et al. (2018) also focus on long-run changes in market volatility and find empirically that loading on these changes helps explain the value effect and moderately contributes to explaining the idiosyncratic volatility discount. While our model does not distinguish between long-run and short-run volatility components, our empirical work uses FVIX as the market volatility factor. FVIX mimics changes in the VIX index, and the VIX index is implied volatility of options on S&P 100 that have roughly one month till expiration. Thus, FVIX factor is likely to pick up the short-run volatility component, and splitting market volatility into long-run and short-run volatility component can differentiate between our results and those of McQuade (2018) and Campbell et al. (2018).

Another advantage of using the C-GARCH-based factors is that VIX picks up, in addition to volatility forecast, other things like expected risk-aversion and changes in volatility risk premium. The disadvantage of using the C-GARCH-based factors is that the volatility forecast imbedded in VIX includes all relevant information that is available to market participants, whereas C-GARCH forecast only uses the information the econometrician can derive from market returns.

Thus, on the one hand, C-GARCH-based factors are expected to be less helpful that FVIX. On the other hand, to the extent they are helpful, they provide a lower bound on the explanatory power of the part of FVIX that is related to changes in expected market volatility and not changes in risk aversion.

In Table 10A, we compare performance of several models: the volatility factor model with FVIX and FIVol, the three-factor ICAPM of Adrian and Rosenberg (2008), as well as Adrian and Rosenberg (2008) and model augmented with FVIX, or both FVIX and FIVol. Panel A looks at the alphas of the five arbitrage portfolios we considered in Tables 5A, 6A, and 8A. The first two columns (columns zero and one) reproduce the two columns of Table 5A and report the alphas from the CAPM and the volatility factor model with FVIX and FIVol. On average, the volatility factor model explains 100% of the CAPM alphas (77-96 bp per month, with the exception of HML alpha, which is 31 bp in the CAPM to start with).

Column two of Panel A presents the alphas from the Adrian-Rosenberg model: the alphas of all portfolios but HMLh decrease, compared to the CAPM, by about 40% (about 30-40 bp per month), and the alpha of HMLh does not decrease at all. Adding FIVol and FVIX to the Adrian-Rosenberg model in columns three and four has the same effect as adding FIVol and FVIX to the CAPM: FIVol largely explains the alphas of HML and HMLh, FVIX largely explains the alphas of IVol, IVolh, IVol55. Column five presents the alphas from the Adrian-Rosenberg model with both FVIX and FIVol added and records the alphas very similar to, albeit somewhat more positive than volatility factor model alphas. Overall, Panel A of Table 10A suggests that the short-run and long-run volatility factors of Ardian and Rosenberg (2008) overlap with FVIX and FIVol, but also do not have additional explanatory power compared to FVIX and FIVol, just borrowing a fraction of theirs.

We conclude from the performance of the Adrian-Rosenberg model that, most importantly, the significantly negative loadings of low-minus-high IVol portfolios and even the negative loading of HML on volatility risk factors are preserved if we use short-run volatility factor from C-GARCH. This factor explains about 40% of the idiosyncratic volatility discount, which is the lower bound of the role played by changes in market volatility in explaining the idiosyncratic volatility discount.

In Panel B of Table 10A, we look at the volatility risk betas from the models described above. We come to two main conclusions. First, in the Adrian-Rosenberg model (Model 2 in the table), it is the short-run component of market volatility (SR) that helps explain the idiosyncratic volatility discount and the value effect. The loadings of the arbitrage portfolios on the long-run component (LR) have the "wrong" sign - i.e., the sign that would make the alphas of the arbitrage portfolios even larger.

Second, adding FVIX and FIVol to the Adrian-Rosenberg model (Model 5 in the table) reveals some overlap between SR and FVIX, but not SR and FIVol. Both SR and FVIX usually remain significant in the presence of one another, so there is value-relevant information in the short-run component of market volatility that is not in VIX, and vice versa. However, when we compare in Panel A the alphas from Model 5 (SR, LR, FVIX, FIVol) and Model 1 (FVIX and FIVol), we find very little difference, which suggest that even if there is information in SR that is unrelated to FVIX, this information is not particularly helpful in explaining the idiosyncratic volatility discount and the value effect.

We conclude from the overlap between FVIX and SR and the inability of LR to explain the value effect and the idiosyncratic volatility discount that our empirical results are different from the theoretical prediction of McQuade (2018) and the empirical results of Campbell et al. (2018).

3.3 Average Total Volatility Factor of Chen and Petkova (2012)

Chen and Petkova (2012) follow a different route and argue that innovations to market volatility appear not to be priced because the true state variable is average total volatility, not market volatility. (Average total volatility is the average total (systematic and non-systematic) volatility of all individual stocks). Chen and Petkova disaggregate market volatility into average total volatility and average correlation between individual stocks and show that average total volatility is priced and average correlation is not. Chen and Petkova also show that the average volatility factor helps to explain the idiosyncratic volatility discount of Ang et al. (2006).

In Panel A of Table 10A, column six looks at the alphas from the two-factor model with the market factor and the factor-mimicking portfolio for the innovations to average total volatility[3]. Somewhat unexpectedly, we find that the average volatility (AV) factor has virtually no ability to explain any of the effects in the table, including the idiosyncratic volatility discount, which was the focus of Chen and Petkova (2012). In the column seven, we also find that there is virtually no overlap between FVIX and the average volatility factor. While inconsistent with the results in Chen and Petkova (2012), the evidence in columns six and seven is consistent with Herskovic et al. (2016), who use a similar average volatility factor and find that it is priced, but cannot explain the idiosyncratic volatility discount.

The cause of the difference between Table 10A and Chen and Petkova (2012) is the absence of innovations to average correlation in our analysis. Chen and Petkova use average correlation as a factor despite their finding that it is not priced. They also use average correlation to create base assets for the factor-mimicking portfolio that tracks innovations to average volatility. While we use as base assets quintile portfolios sorted on

[3]We thank Ralitsa Petkova for sharing the innovation to average total volatility series.

past sensitivity to innovations in average volatility, Chen and Petkova use as base assets five-by-five quintile sorts on past sensitivity to average volatility and average correlation. As a result, their factor-mimicking portfolio for innovations to average volatility has the factor risk premium of -63 bp per month, while our version of their average volatility risk factor has the factor risk premium of -15 bp per month (still statistically significant). The strong dependence of performance of the average volatility factor of Chen and Petkova on the unpriced characteristic - average correlation - is surprising and suggests that probably average volatility is not the state variable behind market volatility.

Contrary to Chen and Petkova, in Panel B of Table 10A, the same two-factor model that produced the alphas in the sixth column of Panel A finds no evidence that arbitrage portfolios capturing the idiosyncratic volatility discount load on the AV factor, but we do find that the AV factor can contribute to explaining the value effect, consistent with our result that the closely related FIVol factor partly explains the value effect, but not the idiosyncratic volatility discount. Also, in the model with AV, FVIX, and FIVol factors (the same model that produced the alphas in the seventh column of Panel A), the AV factor beta remains (marginally) significant for HML and HMLh, but suffers a larger reduction than the loading on FIVol, suggesting that FIVol is a better version of the AV factor.

3.4 Volatility Risk in a Longer Sample

As the previous subsection suggests, using VIX has significant advantages in comparison to using other volatility forecasts, but these advantages come at the cost of reducing the time-series sample, since VIX is available starting in 1986. In this subsection, we make two attempts to extend the sample to 1963-2017.

Panel A of Table 11A tries using the Adrian and Rosenberg (2008) market volatility factors, SR and LR, in the longer sample, since SR and LR are available whenever the market return is available. Column one re-estimates the CAPM in the longer sample, confirming that the IVol discount and value effect are of comparable magnitude in 1963-2017 and 1986-2017 (the CAPM alpha of HML becomes significant in the longer sample). The next three columns report the alphas, SR betas and LR betas from the baseline Adrian-Rosenberg model (the model also has the market factor, but market betas are unreported to save space). Similar to the short sample (1986-2017), we find that SR is useful in explaining the IVol discount (in the longer sample it explains up to 44-71% of the CAPM alphas), but not as useful in explaining the value effect (the alpha of HML is 44% smaller in the Adrian-Rosenberg model compared to the CAPM, but the alpha of HMLh is little changed). LR, on the other hand, tends to have the "wrong sign" and only makes the IVol discount harder to explain, though it helps a little with explaining the value effect. In terms of alpha significance, the alphas of HML, IVolh, IVol55 remain marginally significant in the AR model, IVol alpha becomes insignificant, and the HMLh alpha is highly significant.

In the last four columns, Panel A reports the alphas and volatility risk betas from the AR model augmented with FIVol (FVIX is not available in 1963-85). The new model, AR4L, handles HML and HMLh rather well, confirming the power of FIVol to explain the value effect in the longer sample. The reduction in the IVol discount is now smaller, with AR4L alphas of IVol, IVolh, IVol55 being significant and only 21-43% smaller than the CAPM alphas, and a likely culprit is FIVol, which produces betas of the opposite sign compared to SR. Panel B of Table 11A, discussed below, shows that this problem existed in our baseline volatility factor model as well, but the magnitude of the problem was smaller.

In Panel B, we attempt to backfill FVIX to 1963 using the coefficients from the factor-mimicking regression in 1986-2017. Since the coefficients are rather stable and since investors probably had an idea of what expected market volatility was before VIX (after all, the same investors were setting the values of VIX once VIX started being reported), this backfilling can potentially work well. The main problem with backfilling FVIX is that we do not have the base assets that are being multiplied by the slopes to form the factor-mimicking portfolio. Our base assets are quintile portfolios pre-sorted on historical sensitivity to VIX changes, and this sensitivity is impossible to estimate pre-1986, when VIX is not available.

The choice of base assets is important for factor-mimicking procedure. First, the larger the spread between factor-mimicking portfolios in terms of sensitivity to the state variable (change in VIX, in our case), the better. Second, factor-mimicking portfolios should ideally be devoid of any additional factor structure, which may contaminate FVIX and cause it pick up other factors. Thus, if we replace the base assets we use in the paper (quintile portfolios pre-sorted on historical sensitivity to VIX changes) with a sort on an anomaly variable (e.g., size sorts), we will violate the second requirement; if we replace the base assets with something that clearly does not have factor structure (e.g., industry portfolios), we may violate the first requirement.

Another consideration is that if the base assets are not constructed based on historical sensitivity to VIX changes, the coefficients in the factor-mimicking regression may start to change because the composition of the base assets changes. If we pre-sort firms on historical sensitivity to VIX changes, we can be sure that the top quintile has the lowest amount of volatility risk. If we use, e.g., industry portfolios, we have to consider the possibility that a certain portfolio (oil companies or car manufacturers) can be rich in growth options and thus a good hedge against volatility risk in one decade, but not the other.

Yet another consideration is that the full-sample factor-mimicking regression we perform following the tradition in the factor-mimicking literature starting with Breeden et al. (1989) implicitly assumes that in the beginning of the sample period investors already know the coefficients that the econometrician learns only in the end of the sample period. Presumably, investors had an idea about what expected market volatility was and how to hedge against shifts in that even before VIX is available. In Section 4.1 above, we use a fully tradable version of FVIX, which estimates the factor-mimicking regression using the expanding estimation window and assumes that investors have the same information as the econometrician. We find that the fully tradable FVIX works almost as well as the baseline FVIX. However, the assumption that in the beginning of the sample period investors already know the coefficients that the econometrician learns only in the end of the sample period becomes more and more dubious when the sample period moves further and further into the past, and we cannot create a fully tradable FVIX with the learning sample for the longer 1963-2017 sample, because VIX needs to be available in the learning sample period, and VIX is only available from 1986 onwards.

With all that said, we still attempted to backfill FVIX to 1963 using two-by-three size-BM sorts from Kenneth French's website as the base assets. We ran the factor-mimicking regression for 1986-2017, and then used the coefficients from this regression to form FVIX in 1963-1985. The table on the page above reports the results of using this factor (FVIX63) to explain the alphas of the long-short portfolios from Table 5A.

The long-short portfolios are HML (the Fama-French value-minus-growth factor), IVol (long in the lowest IVol quintile and short in the highest IVol quintile) and three more portfolios from five-by-five sorts on IVol and market-to-book (see Table 4A for full sorts). IVolh is long in lowest IVol growth portfolio and short in highest IVol growth portfolio. HMLh is long in highest IVol value and short in highest IVol growth portfolio. IVol55 is long in high IVol growth portfolio and short in one-month Treasury bill.

The first four columns of Table 11A repeat Table 5A and present the CAPM alphas of the long-short portfolios in 1986-2017 and the alphas, FVIX betas and FIVol betas from the volatility factor model (the market betas are, as usual, suppressed to save space). The volatility factor model in columns 2-4 uses the baseline FVIX with base assets being quintile portfolios pre-sorted on historical sensitivity to VIX changes.

Columns five to seven repeat, in the same 1986-2017 sample, the volatility factor model with the new base assets for FVIX (two-by-three size-BM sorts). We observe that while the FVIX63 betas in column six are similar to FVIX betas in column three, and their significance generally improved, the alphas in column five became by roughly 15 bp larger than the alphas in column two, while still staying insignificant. The slight deterioration in the alphas is consistent with the new base assets being suboptimal for the factor-mimicking procedure.

The four rightmost columns (columns eight to eleven) present the CAPM alphas (column eight) in the longer 1963-2017 sample followed by the volatility factor model in the longer sample (columns nine to eleven). The 1963-2017 CAPM alphas are on average quite close to the 1986-2017 CAPM alphas in column one, with the value effect being somewhat (15 bp) stronger and the IVol discount being about the same. The t-statistics for the alphas are larger due to the sample being longer.

For the reasons described above, the alphas deteriorate further and increase by another 25 bp compared to column five (the volatility factor model with FVIX63 and FIVol in 1986-2017). The deterioration of the alphas affects the IVol discount more, because FVIX was the main force explaining it. The alphas of IVol, IVolh, IVol55 portfolios are now significant - though they are still 30-50% smaller than the CAPM alphas. The alphas of HML and HMLh are insignificant, indicating that the explanatory power of FIVol is the same in 1986-2017 and 1963-2017.

The FVIX63 betas of IVol, IVolh, IVol55 are still highly significant and their magnitude is similar to the one observed in the shorter 1986-2017, so the one of the main conclusions of our paper about the relation between market volatility risk and the IVol discount remains intact. The reason why the volatility factor model with FVIX63 and FIVol works worse in the longer sample is that FVIX63 has lower risk premium (its Carhart alpha is at -19 bp per month, t-statistic -3.10 in the full sample vs. -33 bp per month, t-statistic -3.65, in 1986-2017. The lower risk premium is consistent with the factor-mimicking procedure working poorly in the first (backfilling) years of the sample for the reasons described above.

In Panel C, we switch to looking at whether backfilled FVIX can explain returns to arbitrage portfolios from Table 4 in the paper, which come from double sorts on price-to-cash-flow and IVol rather than double sorts on market-to-book and IVol. The first column re-estimates the CAPM alphas in the longer 1963-2017 sample. The next two columns try to explain the alphas by using only FVIX63, without FIVol. We find, similar to Table 4 in the paper, that FVIX betas of all arbitrage portfolios (except for value-weighted VMG) are statistically significant. When used alone, FVIX63 can explain, on average, 44% of the CAPM alphas. FVIX is also not as successful in explaining the value effect, but in equal-weighted returns explains 83-90% of the IVol discount and its relation to price-to-cash-flow.

The three rightmost columns of Panels B and C report alphas and betas from our three-factor volatility model (market betas are omitted for brevity) estimated in 1963-2017. The three-factor model can explain 52.4% of the alphas and all FVIX betas are still significant (the FVIX beta of value-weighted VMG improves in the presence of FIVol). The change in the alphas is sizeable, and half of them are rendered insignificant, though in 1986-2017 our model performs much better, explaining 92.3% of the CAPM alphas and making all alphas insignificant, since the baseline FVIX is formed in an optimal way (in contrast to FVIX63).

Overall, we conclude that backfilling FVIX is feasible and doing so produces results consistent with what we find in the sample with available VIX, but the backfilled FVIX seems suboptimal, and we decided against using it in the main body of the paper.

4 Aggregate Volatility Risk and Other Asset-Pricing Factors

4.1 Profitability Effect and Aggregate Volatility Risk

4.1.1 RMW Factor and Aggregate Volatility Risk

Barinov (2020) analyzes the overlap between the profitability effect of Haugen and Baker (1996) and Novy-Marx (2013), which is the basis of the new RMW factor in Fama and French (2015). Barinov (2020) shows that the FVIX factor completely explains the alpha of RMW factor, but not the other way around, and suggests an explanation: unprofitable firms are usually distressed, their equity is similar to a call option on the assets, and the option's value, all else fixed, responds positively to increases in volatility and thus provides a hedge against aggregate volatility increases. The RMW factor shorts unprofitable firms and therefore is exposed to aggregate volatility risk, which explains its positive alpha and explanatory power.

Table 12A reproduces Table 2 from Barinov (2020) in slightly longer sample. Panel A reports the alphas of RMW from the CAPM, three-factor Fama-French model, and Carhart (1997) model, which come out between 39 and 50 bp per month with t-statistics exceeding 3. When Panel A adds FVIX to any of the models, the alphas lose significance and decline to 12-18 bp per month, due to FVIX beta of RMW being a highly negative and significant number.

In the spirit of spanning tests in Barillas and Shanken (2017), Panel B performs the regression in Panel A "in reverse" by putting FVIX on the left-hand side and trying to explain its alpha with RMW and other factors. Columns two, three, and six report the alphas of FVIX in the CAPM, three-factor Fama-French model, and Carhart model. The alphas fall into a tight range between -44 and -46 bp per month, with t-statistics exceeding 3.9 by absolute magnitude. Columns four and seven add RMW to the three-factor Fama-French and Carhart models and the RMW beta of FVIX reveals the same significantly negative link between FVIX and RMW as Panel A. However, in Panel A FVIX was able to explain the alpha of RMW, and in Panel B RMW reduces the alpha of FVIX by roughly 9 bp per month and leaves it significant with t-statistics -3.72 and -3.75. Columns five and eight further attempt adding CMA to the models in columns four and seven, but the overlap between FVIX and CMA, while statistically significant, is even smaller - adding

CMA reduces the alpha of FVIX by 4 bp per month.

The conclusion from Table 12A is that FVIX can explain RMW, but not the other way around, and hence FVIX is the risk behind RMW. In other words, RMW substitutes empirically for FVIX, and if an anomaly is explained by RMW, the anomaly is likely to be explained by aggregate volatility risk. Another implication of Table 12A is that using FVIX and RMW together is suboptimal, since those two factors have a significant overlap.

In untabulated results, we also attempt adding FIVol to Panel A and find that RMW loads on FIVol negatively (as on FVIX), but insignificantly in both statistic and economic terms. Likewise, we attempt re-running Panel B with FIVol used on the left-hand side instead of FVIX and find that the change in the three-factor or Carhart alpha of FIVol is visibly smaller when RMW and CMA are added compared to the original Panel B. We conclude that there is little overlap between FIVol and RMW, in contrast to the overlap between FVIX and RMW documented in Barinov (2020).

Lastly, we remark that the relation between RMW and FVIX makes it harder for FVIX to explain the value effect, since growth firms, on average, are more profitable than value firms, and this fact introduces a positive bias to the FVIX beta of HML. If we had a measure of the value effect that is net of profitability/distress effects, we would likely find the negative FVIX beta of HML our model predicts.

4.1.2 RMW, FVIX, FIVol, and Explaining the Anomalies

Another reason why the paper is adding FVIX and FIVol to the CAPM rather than any other benchmark model, beyond potential overlap between RMW and FVIX (as well as the overlap between HML and FIVol the paper discovers) is that the volatility factor model with the market factor, FVIX and FIVol is derived from our theoretical model.

Still, Table 11A reports the results of adding FVIX to the three-factor and five-factor Fama and French (1993, 2015) models to gauge the amount of intersection between FVIX/FIVol and HML/RMW in our application. We do not report the results of adding FVIX to the Carhart model, since Panel A of Table 12A reports that FVIX is nearly orthogonal to the momentum factor. In the first column of Table 11A, we collect the three-factor alphas of the eight arbitrage portfolios (the ninth portfolio, HML, is dropped, because HML is one of the factors in the Fama-French models). The alphas in the first column are already reported in various places in the paper, so the point of the first column is to present them all together as a benchmark.

The next three columns add FVIX and FIVol to the three-factor Fama and French (1993) model and report the alphas and FVIX/FIVol betas. The alphas in the three-factor Fama-French model augmented with FVIX and FIVol are somewhat larger than in the volatility factor model, but compared to the standard three-factor Fama-French model without FVIX and FIVol the alphas of the arbitrage portfolios decline by about 75% (from 72 bp per month average to 18 bp per month average), and only one of the alphas remains marginally significant.

In third and fourth columns of Table 11A, FVIX betas of all low-minus-high idiosyncratic volatility strategies and FIVol betas of all value-minus-growth strategies are negative and significant, as they are in the paper. Compared to similar betas in the volatility factor model (reported in the paper), the significantly negative FIVol betas in columns three and four are smaller by roughly 40%, indicating the overlap between HML and FIVol. The FVIX betas, on the other hand, do not change systematically - the FVIX beta of IVol and IVolh portfolios in column three of Table 11A are about 60% of similar betas in the volatility factor model (see Table 5A), but the FVIX beta of IVol IO and HML IO portfolios in column three of Table 11A more than doubles compared to Tables 5 and 6 in the paper. On average though, FVIX beta of the eight portfolios is about the same in the three-factor Fama-French model augmented with FVIX and FIVol and in the volatility factor model with the market factor, FVIX, and FIVol.

Column five of Table 11A adds the CMA (investment) factor to the three-factor Fama-French model and finds that CMA does not contribute much to explaining the alphas of the eight arbitrage portfolios - on average, the alphas are down by just 7 bp per month compared to the three-factor Fama-French model and only one of them loses significance.

Columns six to eight add FVIX and FIVol to the three-factor Fama-French model augmented with CMA and report the alpha and FVIX/FIVol betas. Column six looks the alphas and concludes that controlling for CMA does not change the explanatory power of FVIX and FIVol, since the decline in alphas between columns five and six is almost exactly the same as between columns one and two. This conclusion is supported by FVIX and FIVol betas in columns seven and eight, which are almost exactly the same as the ones in columns three and four.

Column nine adds to the three-factor Fama-French model the RMW (profitability) factor instead of CMA and reports the alpha. The RMW factor is much more efficient in explaining the alphas of the eight anomalous portfolios: their average absolute alpha is at 43.6 bp per month, as compared to 72 and 65 bp per month in columns one and five, respectively.

Comparing column nine with column two, we can see that FVIX and FIVol are more effective than RMW in explaining the value effect, the IVol discount, and their cross-section, as adding them to the three-factor Fama-French model makes the average absolute alpha decline to 18 bp per month versus 43.6 bp per month average brought about by adding RMW to the three-factor Fama-French model. Column two produces one marginally significant alpha; column nine produces five significant ones.

Column ten reports the alpha from the six-factor model that adds FVIX and FIVol to the model in column nine (market, SMB, HML, RMW). The alphas reveal a strong overlap between RMW and FVIX, as in Barinov (2020) and Table 12A. When we add FVIX and FIVol to the three-factor Fama-French model, the alphas change between the average absolute value of 72 bp per month in column one to 18 bp per month in column two. When we add FVIX and FIVol to the three-factor Fama-French model already augmented with RMW, the average absolute alpha changes from 43.6 bp per month in column nine to 10.7 bp per month.

The comparison of FVIX and FIVol betas in columns three and four versus the ones in columns eleven and twelve shows that controlling for RMW does not impact much the FIVol betas of the eight anomalous portfolios (consistent with the lack of overlap between FIVol and RMW discussed above). FVIX betas in the presence of RMW are, on average, 30% smaller; seven of them retain significance, one gains significance in column nine (HMLh portfolio), and one loses significance (HML Sh). We conclude that while RMW picks up some information in FVIX, FVIX has some information that is not in RMW, consistent with Table 12A.

Columns 13 and 14 report the alphas from the five-factor Fama-French (2015) model and the five-factor model augmented with FVIX and FIVol, respectively. Using CMA and RMW together further reduces the average absolute alpha of the eight anomalous portfolios, to 31 bp per month. Three of the alphas remain significant, and two more are marginally significant at the 10% level. However, this is still behind column two (the three-factor Fama-French model augmented with FVIX and FIVol) and the volatility factor model (the market factor, FVIX, and FIVol) in the paper, which produce the average alphas of 18 and 9 bp per month, respectively, with one (none) of the alphas being marginally significant.

Columns 15 and 16 present FVIX and FIVol betas from the five-factor Fama-French model augmented with FVIX and finds that negative FIVol betas in column 16 are very close to the ones in column twelve (in which FVIX and FIVol are added to the three-factor Fama-French model augmented with RMW), and the same is largely true about comparison of FVIX betas in columns 15 and eleven. This similarity in betas confirms again the lack of overlap between CMA and FVIX/FIVol, and the fact that the difference between alphas of the anomalous portfolios in the three-factor and five-factor Fama-French models comes primarily from the overlap between FVIX and RMW.

4.2 Lottery Factor (FMAX) vs. FVIX and FIVol

Bali et al. (2011) suggest that the idiosyncratic volatility discount has a strong overlap with the MAX effect they document, i. e., the negative cross-sectional relation between maximum daily return in the past month (MAX) and future returns. Bali et al. (2017) attribute the pricing of MAX to lottery preference and suggest using FMAX, an arbitrage portfolio long in top 30% of firms in terms of MAX and short in the bottom 30% of firms in terms of MAX, as a lottery-demand factor, dubbed FMAX. (For the purposes of forming FMAX, MAX is defined as the average of the five highest daily returns in a month rather than just one highest daily return). Bali et al. (2017) show that FMAX can explain the betting-against-beta anomaly of Franzini and Pedersen (2014).

Panels A-C of Table 13A perform the spanning test recommended by Barillas and Shanken (2017) by first using FIVol and FVIX to explain FMAX (Panel A), and then using FMAX to explain FVIX and then FIVol (Panels B and C, respectively). Panel A shows that FVIX can perfectly explain FMAX, reducing its alpha from 53-75 bp per month with t-statistics above 3.5 to 5-17 bp per month, t-statistics below 1.3. FIVol, on the other hand, does not seem to be related to FMAX. The ability of FVIX to explain FMAX is consistent with Barinov (2017), who find that FVIX can explain the maximum effect of Bali et al. (2011).

Panel B shows that FMAX, on the other hand, has a significant overlap with FVIX, but cannot explain its alpha entirely, reducing it from negative 44-46 bp per month, t-statistics greater than -3.9 by absolute magnitude, to still significant negative 29-32 bp per month, t-statistics above -3 by absolute magnitude. This result does not change if we use the fully tradable FVIXT from Tables 7A and 8A instead of FVIX. Panel C confirms that FIVol and FMAX are unrelated: FMAX beta of FIVol is insignificant, and controlling for FMAX does not change the alpha of FIVol irrespective of the model FMAX is added to.

Panels D and E of Table 13A use FMAX to explain the alphas of the five arbitrage portfolios from Table 5A that capture the idiosyncratic volatility discount (IVol, IVolh, IVol55) and the value effect (HML, HMLh). The first four columns of Panels D and E repeat Table 5A and report the CAPM alphas of those portfolios, the alphas from the volatility factor model with the market factor, FVIX and FIVol, as well as the FVIX betas and FIVol betas of the arbitrage portfolios from the same volatility factor model.

Columns five and six report alphas and FMAX betas of the arbitrage portfolios from the two-factor model with the market factor and FMAX. We observe that FMAX can explain the idiosyncratic volatility roughly to the same extent as FVIX and FIVol, but has trouble with explaining the alpha of HMLh, consistent with the lack of overlap between FMAX and FIVol and the leading role FIVol takes in explaining the value effect.

The rightmost four columns of Panels D and E add FMAX to the volatility factor model and observe a strong overlap between FVIX and FMAX, with FVIX betas significantly reduced compared to the original volatility factor model in columns two to four. However, the alphas from the volatility factor model with and without FMAX (columns two and seven, respectively) are usually within a few bp of each other, with equal-weighted HMLh being the only exception (it has large and significant alpha in the four-factor model with the market factor, FVIX, FIVol, and FMAX). The closeness of the alphas suggests that FMAX does not have any additional information (at least about the anomalies in question) to the one already in FVIX and FIVol. Coupled with the ability of FVIX to span FMAX, but not the other way around (see Panels A and B of the same Table 13A), this conclusion suggests that FMAX is just an empirical substitute for FVIX, probably a cleaner one due to the lack of estimation error, but likely a narrower one in terms of information content.

4.3 Aggregate Volatility Risk Factors, Liquidity Risk, and Funding Liquidity

Panel A of Table 15A reports partial correlations, conditional on the market return, between FVIX, FIVol and different measures of market-wide liquidity and funding liquidity, such as the Sadka (2006) liquidity factors (PV_{Sadka} and TF_{Sadka}), TED spread, the broker-dealer leverage factor from Adrian et al. (2014), etc. Since FVIX and FIVol are countercyclical by construction, we expect their correlations with funding liquidity measures to be positive, since funding liquidity measures measure tightness of credit constraints for arbitrageurs. The correlations with liquidity risk factors are expected to be negative, as those factors are formed so that their high values correspond to liquid market.

A cursory glance at the first two columns of Panel A does not reveal a clear pattern along those lines. For example, FVIX seems to be unrelated to liquidity risk factors of either Pastor and Stambaugh (2003) or Sadka (2006), while FIVol does show signs of picking up liquidity risk: high FIVol returns seem to happen in illiquid market even after the negative correlation between FIVol and the market return is accounted for.

FVIX also seems, if anything, negatively related to credit constraints controlling for the market return: partial correlations of FVIX and TED spread and of FVIX and equity capital ratio of financial intermediaries from He et al. (2017) are significantly negative, and hence FVIX loses when TED spread increases, which makes FVIX, a hedge against market volatility risk, exposed to funding liquidity risk (so a positive FVIX beta that is used in the paper to explain the negative alpha of high idiosyncratic volatility firms also implies exposure to funding liquidity risk).

Partial correlations of FIVol with funding liquidity constraints measures send a mixed message. On the one hand, controlling for the market return, FIVol is positively correlated with TED spread and the broker-dealer leverage factor from Adrian et al. (2014), which makes possible the interpretation of positive FIVol betas of growth firms as both a sign that growth firms are a hedge against average idiosyncratic volatility risk and a sign that growth firms are a hedge against funding liquidity risk. On the other hand, partial correlations of FIVol with funding liquidity factors in He et al. (2017) are negative and lead us to the opposite conclusion that positive FIVol betas of growth firms suggest that growth firms are a hedge against funding liquidity risk.

Panels B and C regress FVIX and FIVol, respectively, on the standard asset-pricing factors and the liquidity risk/funding liquidity risk factors from Panel A. The slopes on the asset pricing factors are suppressed and only the intercepts (which are also alphas when tradeable factors such as VW_{PS} and INT_{VW} are used) and the slopes on the liquidity risk/funding liquidity risk factors are reported.

Panel B reports that all loadings of FVIX on liquidity risk/funding liquidity risk factors are insignificant, with both being almost exclusively positive. The alpha of FVIX in the VW_{PS} and INT_{VW} is also very close to the one reported in the paper, so controlling for liquidity risk or funding liquidity risk does not explain why FVIX is priced.

Panel C, to the contrary, finds uniformly negative loadings of FIVol on the same risk factors, however, only loadings on the Pastor and Stambaugh (2003) traded factor are consistently significant (irrespective of whether I add the Pastor-Stambaugh factor to the CAPM, the three-factor Fama-French model, or the Carhart model). The negative loading implies that FIVol is a hedge not only against increases in average idiosyncratic volatility, but also against market illiquidity. However, controlling for liquidity risk in FIVol leaves its alpha large and significant: for example, the Fama-French alpha of FIVol is -95 bp per month in Panel C of Table 1 in the paper and -79 bp per month in Panel C of Table 15A.

We conclude from Table 15A that neither FVIX nor FIVol are likely to pick up liquidity risk or funding liquidity risk in a significant fashion, and our result that growth firms and high idiosyncratic volatility firms are hedges against aggregate volatility risk cannot be reinterpreted as evidence that negative alphas of these firms are driven by their low liquidity risk or low funding liquidity risk.

4.4 FVIX, FIVol, and Stambaugh and Yuan (2017) Mispricing Factors

Stambaugh and Yuan (2017) find that a four-factor model with the market factor, a modified size factor (SMBSY), and two mispricing factors (MGMT and PERF) performs better than several conventional asset-pricing models and explains a number of anomalies. MGMT is a combination of several anomalies (such as the accrual anomaly of Sloan, 1996, the cumulative issuance anomaly of Daniel and Titman, 2006, etc.) that reflect investors' misunderstanding of firm management actions, and PERF is a combination of several anomalies related to firm's performance (e.g., momentum, O-score-based distress risk puzzle of Dichev, 1998, etc.).

A recent paper by Detzel et al. (2019) shows that the four-factor model of Stambaugh and Yuan (2017) can explain the idiosyncratic volatility effect in the long 1967-2016 sample, though not necessariy in the original Ang et al. (2006) sample. We thus explore in this section whether FVIX and FIVol overlap with the new factors suggested by Stambaugh and Yuan (2017) and whether our result that FVIX and FIVol explain the idiosyncratic volatility discount is different from what Detzel et al. (2019) find.

Table 16A performs spanning tests in the spirit of Barillas and Shanken (2017): Panels A-C use FVIX and FIVol to explain the alphas of the three factors (SMBSY, MGMT, PERF) introduced by Stambaugh and Yuan (2017), and Panels D and E attempt to explain the alphas of FVIX and FIVol, respectively, by using SMBSY, MGMT, PERF.

Panel A finds that, expectedly, SMBSY loads positively on FVIX, which makes the positive alpha of SMBSY even bigger. As our paper finds, the low-minus-high idiosyncratic volatility portfolio loads negatively on FVIX, which largely explains its positive alpha. Since highly volatile firms are usually small, the low-minus-high idiosyncratic volatility position is essentially a big-minus-small position, so putting it in reverse, as SMBSY does, results in a positive FVIX beta. Or, to put it another way, if FVIX can explain why low idiosyncratic volatility (big) firms beat high idiosyncratic volatility (small) firms, it will make more puzzling the general tendency of small firms beating big firms, which is behind the SMBSY factor. Panel A also reports that SMBSY and FIVol are largely unrelated.

Panel B looks at alphas of PERF and finds that when SMB and HML are controlled for, FVIX can make a moderate contribution to explaining those: for example, the alpha of PERF in the three-factor model is 104 bp per month, and once we add FVIX, the FVIX beta of PERF is negative and significant at -0.458 and the alpha of PERF drops to 93 bp per month. FIVol, again, is largely unrelated to PERF.

Panel C of Table 16A considers MGMT factor and finds a somewhat stronger relation between MGMT and FVIX, while still finding no relation between MGMT and FIVol. For example, adding FVIX to the CAPM reduces the alpha of MGMT from 75.5 bp per month to 47.7 bp per month, while leaving it highly significant. Once SMB and HML are controlled for, though, the effect of FVIX on MGMT alpha is within 10 bp per month, as in Panel B, though FVIX betas of MGMT stay significant even then.

Panel D makes FVIX the dependent variable and finds, consistent with the limited overlap between FVIX and PERF/MGMT, that the Stambaugh and Yuan (2017) model produces lower alpha of FVIX than other conventional models: while the CAPM, the three-factor Fama-French model, and the Carhart model all pin the FVIX alpha at negative 44-46 bp per month, the alpha of FVIX in the Stambaugh-Yuan model is -35.4 bp per month, t-statistic -3.47. However, the five-factor Fama-French model produces a very similar and even smaller FVIX alpha of -30.5 bp per month, and adding CMA and RMW to the Stambaugh-Yuan model renders MGMT and PERF insignificant, suggesting that in the case of explaining FVIX MGMT and PERF effectively substitute for RMW (which brings the analysis back to Section 4.1 and Tables 11A and 12A).

Panel E of Table 16A looks at alphas and factor betas of FIVol and finds that the Stambaugh-Yuan model does not contribute to explain the alpha of FIVol. If anything, the mispricing factors, in particular PERF, are contributing negatively, since the PERF beta of FIVol is positive and significant, making the negative alpha of FIVol even more negative (e.g., the three-factor Fama-French model estimates the said alpha at -97.4 bp per month, while the Stambaugh-Yuan model has it at -117.2 bp per month).

Table 17A compares the ability of the volatility factor model and the Stambaugh-Yuan model to explain the anomalies in the paper, represented by the five arbitrage portfolios (HML, HMLh, IVol, IVolh, IVol55). The first six columns in Table 17A repeat Table 5A, reporting, for the five arbitrage portfolios, the CAPM alpha, the Carhart alpha, and the alpha from the three-factor Fama-French model, as well as the alpha and FVIX/FIVol betas from the volatility factor model.

The next four columns report, for the same portfolios, the alpha from the Stambaugh-Yuan model and the three betas on the new factors (SMBSY, MGMT, PERF). I observe, consistent with Detzel et al. (2019), that the Stambaugh-Yuan model can explain away the idiosyncratic volatility discount in the 1986-2017, both in value-weighted (Panel A) and equal-weighted (Panel B) returns. The alphas from the Stambaugh-Yuan model are similar, in the case of IVol, IVolh, IVol55, to the alphas from the volatility factor model. The main driver of the Stambaugh-Yuan model success in Table 17A seems to be the MGMT factor, which produces several times larger betas than PERF (and the sign of SMBSY betas is expectedly backwards and not helpful for explaining the idiosyncratic volatility discount).

The ability of the Stambaugh-Yuan model to explain the value effect is, however, limited. While the Stambaugh-Yuan alpha of HML in Panel A is very close to zero, in

1986-2017 even the CAPM alpha of HML is insignificant to start with. When it comes to explaining the value effect where it is the strongest (i.e., explaining the alpha of HMLh, the value-minus-growth strategy performed in the top idiosyncratic volatility quintile), the Stambaugh-Yuan model produces alphas of roughly 65 bp per month both in equal-weighted and value-weighted returns.

The rightmost six columns add FVIX and FIVol to the Stambaugh-Yuan model and report the alphas and all betas except for the market beta, which is omitted for brewity. We still observe a significant decline, by roughly 20-30 bp per month, in the alphas of the arbitrage portfolios, which is comparable to the difference in the alphas between the three-factor Fama-French model and the volatility factor model. In particular, having the Stambaugh-Yuan factors, FVIX, and FIVol flips the sign of the idiosyncratic volatility discount: the value-weighted IVol and IVolh portfolios post the alphas of -36.5 bp and -59.9 bp per month, t-statistics -2.17 and -2.56.

To sum up, Tables 15A and 16A suggest that while FVIX, but not FIVol, has limited overlap with Stambaugh and Yuan (2017) mispricing factors MGMT and PERF, neither FVIX and FIVol span MGMT and PERF, nor the other way around. Hence, the explanations of the idiosyncratic volatility discount provided by FVIX, on the one hand, and MGMT and PERF, on the other hand, are two different and complimentary explanations. PERF and MGMT also cannot explain the strong value effect for high idiosyncratic volatility firms, a job that is handled well by FIVol.

5 Miscellaneous Additional Results

5.1 Potential ICAPM Interpretation

The model in the paper is a static model, in which aggregate volatility enters the pricing kernel due to nonlinearities in the value of the firms, which make the terminal consumption depend on both market volatility and average idiosyncratic volatility. The pricing kernel holds each period, and then the world in the model resets and starts anew, so there is no hedging demand and intertemporal considerations.

Empirically, however, both market volatility and average idiosyncratic volatility can be thought of as state variables in the ICAPM sense and, in fact, earlier papers showing that those variables should be and are priced (Campbell, 1993, Chen, 2002, Ang et al., 2006 for market volatility, Chen and Petkova, 2012, Herskovic et al., 2016 for average idiosyncratic volatility) treat market volatility and average idiosyncratic exactly this way. Table 2 in the paper also shows that average volatility significantly increases during recessions and periods of high market volatility, and market volatility is known to be higher in recessions at least since Schwert (1989).

Chen (2002) shows that investors appreciate the hedge against volatility increases if volatility increases imply higher future volatility (otherwise there is no need for them to cut current consumption and increase precautionary savings in response to an increase in volatility). If FVIX provides such a hedge, its returns should predict recessions and market volatility. We test this prediction in Panel A of Table 18A.

In the first row, we perform the probit regression of the NBER recession dummy on FVIX. We find that a 1% return to FVIX increases the probability of recession in the current or the next quarters by 0.62-1.15 percentage points. Given that the unconditional probability of recession in our sample is around 10%, it is a large effect, and it becomes even larger if we evaluate it setting FVIX to its 90th percentile rather than mean. We also find that FVIX return can predict recessions for up to a year ahead, but the recession dummy cannot predict the FVIX return.

In the next three rows of Panel A, we use FVIX returns to predict market volatility and vice versa. Consistent with Chen (2002) and the hypothesis that FVIX is a valid ICAPM factor, we find that FVIX returns can predict market volatility for up to a year ahead. A 1% FVIX return corresponds to the increase in the current market volatility by 1.22% to 2.26% and the increase in the future market volatility by 0.53% to 1.05%. We conclude therefore that FVIX is a valid hedge against market volatility increases and the corresponding need to cut current consumption and to increase precautionary spending.

In the last row of Panel A, we look at whether FVIX returns are related to average IVol, and find that the contemporaneous relation between FVIX and average IVol is significantly weaker than a similar relation between FVIX and market volatility, but the ability of FVIX to predict average IVol two quarters into the future is similar to FVIX ability to predict market volatility. We conclude that FVIX can also be a hedge against average IVol.

In Panel B of Table 18A, we perform similar analysis with FIVol. We find that FIVol returns increase prior to recessions and prior to increases in average IVol. A 1% return to FIVol increases the probability of recession by 0.37-0.68 percentage points (as compared to roughly 10% unconditional probability of recession). The relation between FIVol returns and market volatility is weaker and is visible only as a contemporaneous relation. The same 1% return to FIVol leads to an average increase in future average IVol by 0.35% and a current increase in market volatility by 0.88-1.12%. We conclude that FIVol is a good hedge against recessions in general and increases in average IVol in particular, as it should be, and that FIVol also has limited ability to hedge against market volatility risk.

We conclude from the evidence in Table 2 in the paper and Table 18A in this document that both FVIX and FIVol are valid ICAPM factors and negative loadings on these factors can be viewed as desirable because assets with negative FVIX/FIVol betas facilitate wealth transfer from good to bad states of the world: the market-neutral position in such assets gains when the economy slows down and both market volatility and average idiosyncratic volatility increase. Hence, while hedging demand is outside of our theoretical model, our empirical volatility factor model (with the market factor, FVIX, and FIVol) can be also thought of as a three-factor ICAPM.

5.2 Alternative Versions of the Value Effect

The value-minus-growth strategy has been defined in many ways, which fall under the general rule of "short stocks that are expensive according to a certain price multiple, and buy stocks that are cheap according to the same multiple". In addition to the traditional book-to-market, the seminal Fama and French (1992) paper formed the value-minus-growth strategy using earnings-to-price ratio (E/P), dividend yield (D/P), and price-to-cash-flow ratio (CF/P). Several recent papers provided further alternatives to defining value and growth: Asness and Franzini (2012) suggested updating book-to-market on a monthly basis, and rebalancing the portfolio as new data on market cap become available (the so-called "HML devil" strategy). Asness et al. (2015) suggested a composite value strategy that sorts on the average of all four price ratios used in Fama and French (1992). Ilmanen et al. (2019), among other papers, reported that the "cheap-minus-expensive" strategy works across many asset classes, including bonds, currencies, and futures.

In Table 19A, we explore whether FVIX and FIVol can explain the alpha of all those versions of the value-minus-growth strategies. The strategies short the top 30% expensive stocks/securities and buy the bottom 30% cheap stocks/securities. The returns to E/P, D/P, CF/P strategies are from the website of Kenneth French, the returns to the "HML devil" and the HML strategy involving all asset classes are from www.aqr.com.

The first three rows of Table 19A look at the CAPM, Carhart, and five-factor Fama-French alphas of the alternative value-minus-growth portfolios. In our 1986-2017 sample, the value-minus-growth strategy based on E/P or CF/P is more reliable than the standard HML: both strategies turn in significant CAPM alphas of 38.1 bp and 38.5 bp per month, as compared to the statistically insignificant 31 bp per month HML has in Table 5A. The alphas of those two strategies stay significant even in the five-factor model, though their magnitude declines to 15 and 17 bp per month.

The alphas of the strategy based on D/P and the alpha of the "HML devil" strategy are both insignificant, while the composite strategy has a large CAPM alpha of 52 bp per month, which is still at 32.5 bp per month, t-statistic 2.92, in the five-factor model. The "cheap-minus-expensive" strategy that spans several asset classes (HML all) is not as profitable, but equally stable, with significant CAPM and five-factor alphas of 23.2 bp and 17.5 bp per month.

The volatility factor model handles all value-minus-growth strategies well, reducing their alphas to roughly the values produces by the five-factor model (which includes the traditional HML factor) and making all of the alphas insignificant, except for the alpha of the composite strategy. As in the paper, the heavy lifting is done by FIVol: FIVol betas of the value-minus-growth strategies are negative and highly significant with the exception of the strategy based on D/P (the presence of which in the composite strategy is driving the failure of the volatility factor model to completely explain the alpha of the composite value-minus-growth strategy). FVIX beta is only significant for the strategy based on E/P and the "HML all" strategy (and marginally insignificant for "HML devil").

Overall, we conclude that the ability of the volatility factor model to explain the value effect does not depend on the definition of value and growth we use. Particularly interesting is the ability of FVIX and FIVol to explain the alpha of the "HML all" strategy that spans several asset classes. This ability suggests that aggregate volatility risk matters outside of the stock market too, and FVIX and FIVol can help in resolving anomalies in the fixed income, foreign exchange, and derivatives markets.

5.3 Alternative Measures of Growth Options

Table 20A verifies that the link between aggregate volatility risk exposure and growth options exists if we use several alternative measures of growth options. Panel A sorts firms on annual growth rate in total assets, thus avoiding the use of market valuations. The first row of Panel A confirms the presence of positive relation between asset growth and market-to-book by reporting average market-to-book across the asset growth quintiles (the spike in market-to-book of the bottom asset growth quintile is driven by outliers and the relation between asset growth and market-to-book becomes monotonic if we use medians). The next two rows report FVIX betas and FIVol betas from the three-factor volatility model and document significantly positive FVIX and FIVol betas of the top asset growth quintile and significantly negative FVIX and FIVol betas of the bottom asset growth quintile.

Panel B performs similar sorts on PVGO, the fraction of the firm value that comes from future growth opportunities in the Gordon model, as suggested by Bali et al. (2020). PVGO is roughly similar to the negative of cash-flow-to- price ratio with a few tweaks: first, cash flow is defined as earnings minus accruals (rather than earnings minus depreciation), and accruals are estimated as in Sloan (1996). Second, we use expected cash flows rather than observed ones, and the expected value is the fitted value from the fourth-order autoregression of quarterly cash flows (defined as above). Third, the price-to-cash-flow ratio is scaled by a rough estimate of WACC, which differentiates between firms with high and low effective tax rates.

PVGO is monotonically and more reliably related to market-to-book than asset growth in Panel A; FVIX betas are significantly positive/negative for high/low PVGO firms, and FIVol betas change from large and significantly negative values in the bottom quintiles to roughly zero in the top quintile, with the difference being significant with t-statistic 4.72.

Panel C looks to diminish the effect of firm's market value (which can potentially capture mispricing) on the PVGO measure and follows Trigeorgis and Lambertides (2014) in running a panel regression of PVGO on several predictors of growth options importance, such as R&D-to-sales ratio, SG&A-to-sales ratio, leverage, idiosyncratic volatility, idiosyncratic skewness, and market power. Panel C sorts firms on the fitted values from this panel regression, which are our measure of expected/predicted PVGO. The results in Panel C are quite similar to the ones in Panel B: predicted PVGO is strongly and positively related, in cross-section, to market-to-book, FVIX betas, and FIVol betas. The only difference is that Panel C does find positive FIVol beta (hedging ability against increases in average idiosyncratic volatility) in the top PVGO quintile.

Lastly, Panel D sorts firms on the convexity measure TVolSens, suggested by Grullon et al. (2012). TVolSens is the slope from regressions of firm returns on market returns and change in the firm's total volatility. The regressions are performed using data from months t-1 to t-60, and the sorts are performed in month t. The link between TVolSens and market-to-book is generally positive, but rather weak, since TVolSens picks up all convexity, including the one coming from distress, and distress and market-to-book are negatively related. However, the relation between TVolSens and FVIX/FIVol beta is significantly positive.

Overall, Table 20A presents strong evidence that one of our main results that growth firms are hedges against increases in market volatility and average volatility is robust to using different measures of growth options, even those that do not use market valuations or are not that strongly related to market-to-book.

5.4 Exposure to Changes in VIX

The previous sections show that exploiting the idiosyncratic volatility discount and the value effect means negative exposure to the FVIX factor. Because FVIX is the portfolio with the maximum positive correlation with changes in expected aggregate volatility (i.e., changes in VIX), the negative loadings mean that the portfolio long in low volatility firms and short in high volatility firms, as well as the portfolio that buys value and short-sells growth suffer large losses when expected aggregate volatility increases. These losses are larger than what the CAPM would predict, and constitute therefore aggregate volatility risk, which appears to be responsible for both the idiosyncratic volatility discount and the value effect.

In this subsection, we use change in VIX directly to test the hypothesis that low volatility firms and value firms react more negatively to aggregate volatility increases than high volatility firms and growth firms. We use daily data, because, as AHXZ point out, the change in VIX are a much better proxy for the innovation in VIX at the daily frequency than at the monthly frequency.

In Panel A of Table 21A, we report the slopes on VIX change ($\beta_{\Delta VIX}$)in the regression of the arbitrage portfolios returns on the market factor and change in VIX:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta_{\Delta VIX} \cdot \Delta VIX \tag{4}$$

For comparison, we also report FVIX betas from (β_{FVIX}) the same regressions where change in VIX is replaced by daily returns to the FVIX factor:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \beta_{FVIX} \cdot FVIX \tag{5}$$

and the market betas (β_{MKT}) from the simple CAPM fitted to daily returns:

$$Ret = \alpha + \beta_{MKT} \cdot MKT \tag{6}$$

The leftmost column of Table 21A shows that, consistent with our model and the results in the rest of the paper, the portfolios that buy value and short-sell growth or buy low volatility stocks and short-sell high volatility stocks do lose significantly more value in response to increases in expected aggregate volatility than what the CAPM would suggest. For example, $\beta_{\Delta VIX}$ of the value-weighed IVol portfolio is -0.09, t-statistic -7.02, and $\beta_{\Delta VIX}$ of the value-weighed HMLh portfolio is -0.059, t-statistic -3.65. The high volatility growth portfolio also performs better than assets with the same CAPM beta when expected aggregate volatility increases: its value-weighted $\beta_{\Delta VIX}$ is 0.07, t-statistic 4.22.

The FVIX betas in Table 21A, based on daily data, are very similar to the FVIX betas of the same portfolio reported in Tables 4, 5, and 6, and, if anything, the daily FVIX betas are larger and more significant. For example, Table 5A reports monthly FVIX betas of the HMLh and IVol portfolios as -0.837, t-statistic -2.94, and -1.915, t-statistic -4.40, respectively. Table 21A reports similar daily FVIX betas as -0.755, t-statistic -6.62, and -2.184, t-statistic -35.7, respectively.

During recessions, VIX increases by 20 to 40 points, which means that, as the economy goes from expansion to recession, the various cuts of the IVol portfolio underperform the CAPM by 1 to 4 percentage points. For example, the VIX change loading of the value-weighted IVol portfolio is -0.09, which means that if VIX changes by 30 points, the IVol portfolio will trail the CAPM by $0.09\% \cdot 30 = 2.7\%$. Similarly, the loadings on the VIX change of the HML portfolios imply that the value minus growth strategy trails the CAPM by 0.4 to 2.4 percentage points, as the economy goes from expansion to recession.

For comparison, when we regress the excess market return on the VIX change, we find that, according to the regression, the market portfolio loses about 31 bp for each one-point increase in VIX or at most 10 percentage points, as the VIX changes from its expansion level to its recession level. The loading of the market portfolio on the VIX change, as well as the loadings of all portfolios in Table 21A on the VIX change, imply the losses that are much smaller than the real losses suffered by stocks as the economy goes all the way from expansion to recession. This fact, coupled with the higher significance of the FVIX betas, suggests that change in VIX is a noisy measure of unexpected changes in expected aggregate volatility, and low values of change in VIX loadings are the sign of the classical error-in-variables problem.

However, the loadings on the change in VIX give us some idea about the relative importance of the difference in aggregate volatility exposure. For example, it appears that when aggregate volatility increases, the value-weighted IVol portfolio gains because it has a negative market beta, but it gains less than what the CAPM would predict. In the third column of Table 21A, the market beta of the value-weighted IVol portfolio is -0.55, and if we believe that the market portfolio loses around 31 bp per each point increase in VIX, we would predict from the CAPM that the IVol portfolio should gain $0.55 \cdot 31 = 17$ bp per each point increase in VIX. The change in VIX loading of the value-weighted IVol portfolio is -0.09, which means that when VIX goes up by one point, the IVol portfolio trails the CAPM prediction by 9 bp, or changes the gain promised by the CAPM from 17 bp by 9 bp, or by 53%. Similar calculations for other portfolios in Table 21A show that all these portfolios are set to gain from VIX increases because their market betas are negative, but the gain is 20% to 55% smaller than what the CAPM predicts because of their negative loadings on the VIX change.

The observation that the arbitrage portfolios that try to exploit the value effect and the idiosyncratic volatility discount, do not lose during increases in aggregate volatility, but rather gain much less than what the CAPM would predict, is an important one. It underscores the conditional nature of our aggregate volatility story, which "holds everything else fixed". It is also consistent with moderate average raw returns to these portfolios (in 1986-2008, the HML portfolio makes, on average, 32 bp per month, t-statistic 1.46, and the value-weighted IVol portfolio makes 61 bp per month, t-statistic 1.65). The real puzzle of the value effect and the idiosyncratic volatility discount is not why the implied strategies are very profitable (they are not), but rather why these strategies, which have strongly negative market betas, earn non-negative returns. The combination of the negative market betas and the non-negative average returns create the puzzling large positive alphas of the value minus growth and the low minus high idiosyncratic volatility strategies. The negative loadings of these strategies on change in VIX help to explain the negative CAPM alphas by pointing out that the negative market betas severely overstate the performance of these strategies in hard times. Rather than being good, this performance is quite close to zero, which makes the non-negative average returns to the value minus growth and the low minus high volatility strategies much less puzzling.

In Panels B and C, we replace both FVIX and FIVol by changes in VIX and IVol. Since VIX changes are daily, we construct daily average IVol series. We compute daily IVol by estimating IVol from firm-level regressions using 250 previous days and shifting the estimation window one day at a time. The daily IVols of all firms are then averaged each day to form the daily IVol series. The autocorrelation of daily IVol is very close to one, so the daily change is close to innovation to IVol.

Another change we make in Panels B and C is that we switch to the arbitrage portfolios from Table 4 in the paper. Those arbitrage portfolios come from double sorts on price-to-cash-flow and IVol, rather than market-to-book and IVol.

In the first column of Panel B and C, we regress daily returns to the arbitrage portfolios from Table 4 in the paper on daily returns to the market and change in VIX. All slopes on change in VIX are significant and have the same sign as FVIX betas in Table 4 in the paper.

In the next two columns, we add daily change in IVol as the third variable. The two columns show that in the presence of change in IVol, change in VIX is still related negatively and significantly to the arbitrage portfolio returns and positively and significantly to return to the HiVolG portfolio (high IVol growth firms). The same is true about loadings of the arbitrage portfolios on change in IVol: they all have the same signs as the loadings on change in VIX, and in only two cases the loadings are insignificant. This is in fact even better than the results in Table 4 in the paper that uses FIVol and finds that FIVol betas of IVol and IVolG portfolios are insignificant and often have the wrong sign.

In the next two columns of Panels B and C, we use residuals from ARMA(1,1) model fitted to daily IVol instead of change in IVol and arrive to very similar results with even better significance (now only one loading on IVol has t-statistic of -1.6, and all others have t-statistics greater than 2.3 in absolute magnitude).

Overall, in Table 21A we are able to use daily changes in VIX and IVol to reconfirm the conclusions from Table 5A and Table 4 in the paper that high idiosyncratic volatility firms, growth firms, and especially high volatility growth firms react less negatively to increases in expected aggregate volatility than the CAPM predicts, and therefore can be a hedge against aggregate volatility risk.

5.5 Double Sorts on Idiosyncratic Volatility and Market-to-Book: Equal-Weighted Returns

Table 4A presents double sorts on idiosyncratic volatility and market-to-book and reports, for all portfolios, value-weighted CAPM alphas, value-weighted alphas from the volatility factor model with the market return, FVIX, and FIVol, and the FVIX and FIVol betas of all portfolios from the same model. Table 22A, discussed below, reports the same alphas and betas using equal-weighted returns.

Similar to Panel A of Table 4A, Panel A of Table 22A reports the CAPM alphas and finds that the value effect is largely confined to the top idiosyncratic volatility quintile, and the idiosyncratic volatility discount is particulary strong in the top two market-to-book quintiles and absent in the bottom market-to-book quintile. The main driver behind those two patterns is the large negative alpha of the high volatility growth portfolio (the intersection of the top market-to-book quintile and the top idiosyncratic volatility quintile, dubbed IVol55 in Table 5A). In equal-weighted returns, the alpha of the high volatility growth portfolio checks in at -89 bp per month, t-statistic -3.87.

Panel B of Table 22A confirms the conclusion of Panel B of Table 4A that the volatility factor model almost perfectly explains all alphas in the double sorts on idiosyncratic volatility and market-to-book. The alpha of the high volatility growth portfolio declines to -11 bp per month, the alpha of the low-minus-high idiosyncratic volatility strategy in the top market-to-book quintile drops from 115 bp per month in Panel A to mere 9 bp per month, the value effect in the top idiosyncratic volatility quintile is reduced from 109 bp to 30 bp per month, and the difference in the idiosyncratic volatility discount between growth and value firms drops from 96 bp to 15 bp per month as one goes from Panel A to Panel B.

Panel C of Table 22A reports FVIX betas across the double sorts and confirms the result in Panel C of Table 4A: FVIX contributes strongly to explaining the idiosyncratic volatility discount in all market-to-book quintiles, and even more so in the top market-to-book quintile, but only helps to explain the value effect in the top idiosyncratic volatility quintile.

Panel D of Table 22A looks at FIVol betas and again agrees with Panel D of Table 4A: the value-minus-growth strategy has significantly negative FIVol betas (indicating exposure to aggregate volatility risk) in all idiosyncratic volatility quintiles, and those FIVol betas are significantly more negative if the value-minus-growth strategy is followed in the top idiosyncratic volatility quintile. However, FIVol does not seem to contribute to explaining the idiosyncratic volatility discount, since the FIVol beta of the low-minus-high idiosyncratic volatility strategy is insignificant in all market-to-book quintiles.

In total, equal-weighted returns in Table 22A produce very similar results to the ones reported in Table 4A that uses value-weighted returns.

5.6 Idiosyncratic Volatility Discount and Value Effect at Earnings Announcements

Earnings announcement event windows are short (the usual announcement window are three days in a quarter that surround the announcement date), so if an anomaly is risk-driven, only a small part (less than 5%) of the risk premium the anomaly represents will accrue to the trading strategy based on the anomaly during the announcement window. On the other hand, if an anomaly is mispricing, one would expect the mispricing to be partially resolved after investors see the new information in the earnings report, and the returns to the trading strategy implied by the anomaly to be significantly concentrated at earnings announcements.

Sloan (1996) and La Porta et al. (1997) are the first papers to look at anomalies' concentration around earnings announcements. In particular, La Porta et al. look at the value-minus-growth strategy, record only the returns earned by the stocks involved during three days around their earnings announcement date, and find that about one-third of the value effect happens during those three days (different for each stocks). This one-third is the lower bound of the fraction of mispricing in the value effect (the information can hit the market and the mispricing can be resolved during other, non-earnings-announcement days, but those days are harder to identify for all stocks in the sample).

In Table 23A, we perform the same double sorts on idiosyncratic volatility and market-to-book that Table 22A performed and record cumulative abnormal returns (CARs) from the CAPM during the three days surrounding the date of the earnings announcement (from Compustat quarterly files) for all firms in the 25 double-sorted portfolios. The CAPM betas are estimated using daily data in the preceding quarter. Panel A reports value-weighted CARs, and Panel B deals with equal-weighted CARs. The CARs are divided by three to make them comparable to monthly returns in Table 22A and Table 4A.

Comparing Panel A of Table 22A (CAPM alphas in the whole holding period) and Panel B of Table 23A (CAPM-based CARs around earnings announcements), we observe, first, significant idiosyncratic volatility discount realized around earnings announcement date, but only for the top two market-to-book quintiles. The "monthly" values of idiosyncratic volatility discount at earnings announcements are relatively small though: Panel A of Table 22A pegs the total idiosyncratic volatility discount at 115 bp per month, of which 20 bp (in fact, 60 bp) happen during the next earnings announcement. So the part of the idiosyncratic volatility discount that is clearly mispricing is less than 20% of the total.

Similarly, Panel B of Table 22A confirms the La Porta et al. (1997) result that the value effect is concentrated around earnings announcements, and additionally finds that this concentration is stronger in top idiosyncratic volatility quintiles. The fraction of the value effect that is concentrated around earnings announcements is similar to what La Porta et al. report: Panel B of Table 22A reports the total value effect in the top idiosyncratic volatility quintile to be 109 bp per month, of which, according to Panel B of Table 23A, 45.5 bp per month, or 40%, happen around earnings announcements. In value-weighted returns, the concentration is weaker, since Panel A of Table 23A reports that 23 bp of the value effect in the top idiosyncratic volatility quintile happen around earnings announcements.

Overall, we do observe significant signs of mispricing in Table 23A, which explains at least 20% of the idiosyncratic volatility discount and 30-40% of the value effect. This evidence is consistent with the ability of the mispricing factors of Stambaugh and Yuan (2017) to explain an even larger fraction of the two anomalies, and this fraction, as Table 17A suggests, has limited overlap with what FVIX and FIVol can explain.

The mispricing explanation and the aggregate volatility risk explanation of those two anomalies are not mutually exclusive, and the results in the paper suggest that the aggregate volatility risk can explain close to 100% of the two anomalies and thus the aggregate volatility risk explanation is likely to be relatively more important that the mispricing explanation.

6 Behavioral Explanations

Our model does not necessarily imply that the IVol discount/value effect is unrelated to variables other than market-to-book/IVol. It does imply, however, that after we control for FVIX and FIVol, the cross-sectional relation of the IVol discount and value effect to any variable should disappear. In this section, we verify that FVIX and FIVol can explain the relation of the IVol discount and value effect to short-sale constraints proxies.

6.1 Idiosyncratic Volatility Discount, Institutional Ownership, and the Probability to Be on Special

Several recent empirical papers find evidence consistent with the behavioral explanation of the IVol discount. The behavioral explanation is based on the Miller (1977) argument that under short sale constraints firms with greater divergence of opinion about their value will be more overpriced. Miller (1977) argues that short sale constraints keep pessimistic investors out of the market, and the market price reflects the average valuation of the optimists. The average valuation of the optimists is higher than the fair price and naturally increases with disagreement. Therefore, the overpricing should increase in both short sale constraints and disagreement/volatility, and the negative relation between disagreement/volatility and future returns should be the strongest for the most short sale constrained firms.

Consistent with this idea, Nagel (2005) and Boehme et al. (2009) find that the IVol discount is much stronger for the firms they perceive to be the costliest to short. Nagel (2005) uses low institutional ownership (IO) as a proxy for low supply of shares for shorting and thus high shorting costs. Boehme et al. (2009) look at high short interest (high demand for shorting).

We follow Nagel (2005) in looking at residual IO, which is orthogonalized to size (see Data Appendix). We do not have access to the short interest data for the full sample period and use instead the estimated probability that the stock is on special.[4] The exact formula for the probability to be on special is in the Data Appendix. It uses the coefficients estimated by D'Avolio (2002) for a short 18-month sample of the stocks with available data on shorting fees. Ali and Trombley (2006) use the same formula to estimate the probability to be on special for a much longer sample and show that it is closely tied to real shorting fees in different sub-periods.

In Panel A of Table 24A, we look at the low-minus-high IVol portfolios formed separately in each IO quintile. Consistent with Nagel (2005), the top two rows in Panel A find stronger IVol discount for low IO firms. However, after we control for the FVIX and FIVol factors in Panel A, the IVol discount in all IO quintiles goes away. In the lowest IO quintile in Panel A, it declines from 1.175% per month, t-statistic 3.77, to 0.184% per month, t-statistic 0.46. The difference in the IVol discount between low and high IO firms also declines significantly from 69.1 bp per month, t-statistic 2.41, to 24.9 bp per month, t-statistic 0.76.

To find out why the FVIX beta of the low-minus-high IVol portfolio becomes more negative as IO decreases, we also look at IVol in five-by-five sorts on IVol and IO (results not reported to save space). The sorts suggest that institutions face a trade-off between market volatility risk and IVol, trying to avoid both. Thus, the low IO subsample consists of both stocks with the most negative FVIX betas (and lowest IVol) and the most positive FVIX betas (and the highest IVol).

In Panel B of Table 24A, we find similar evidence using estimated probability to be on special. The IVol discount, measured as the CAPM alpha, changes from 38 bp per month, t-statistic 1.79, for the stocks that are the cheapest to short, to 121 bp per month, t-statistic 3.17, for the stocks that are the most expensive to short.

After we control for FVIX and FIVol, the IVol discount disappears in all probability to be on special quintiles. The IVol discount in the quintile with the highest probability to be on special declines to -6.1 bp per month.

When we look at the IVol in the single sorts on estimated probability to be on special (results not tabulated to save space), we find that the most expensive to short stocks have twice higher IVol than the cheapest to short stocks. This is to be expected: the losses from lending volatile stocks are potentially greater, and therefore lenders should charge a

[4] The stock is said to be "on special" when the shorting fee exceeds the risk-free rate.

higher fee. Since stocks with high probability to be on special have higher IVol, sorting these stocks on IVol produces a wider spread in both IVol and aggregate volatility risk.

6.2 Value Effect, Institutional Ownership, and the Probability to Be on Special

Nagel (2005) finds that the value effect is also stronger for the firms with low IO and interprets this result as the evidence that the value effect arises because growth firms are overpriced and some of them are hard to short (for example, when IO and hence the supply of shares for shorting is low).

Analogous to the previous section, we find that institutions prefer to hold firms with intermediate levels of market-to-book and that probability to be on special is much higher for growth firms. Hence, the spreads in market-to-book and, therefore, aggregate volatility risk are mechanically wider if the sorts on market-to-book are performed in the subsample with low IO or high probability to be on special.

In Table 25A, we look at the value-minus-growth portfolios formed separately within each IO quintile (Panel A) or estimated probability to be on special quintile (Panel B). In the top row of each part of Table 25A, we find that the value effect is indeed stronger for the firms with the lowest IO or the highest probability to be on special.

In the third row of each part of Table 25A, we find that controlling for aggregate volatility risk materially reduces the difference in the value effect between stocks that are easy and hard to short. In the IO sorts, the difference in the value effect decreases to 75.7 to 30.7 bp per month, t-statistic 1.01. In the sorts on estimated probability to be on special, the difference decreases from 99.8 to 25.7 bp per month, t-statistic 0.93.

6.3 Arbitrage Asymmetry and the IVol Discount

Stambaugh et al. (2015) argue that the IVol discount arises because of arbitrage asymmetry. If one double-sorts on a comprehensive measure of mispricing and on IVol, Stambaugh et al. argue, the relation between IVol and future returns will be positive for underpriced stocks and negative for overpriced stocks: high IVol underpriced/overpriced stocks have most positive/negative alphas, since IVol is a limits-to-arbitrage proxy. Since shorting is costlier than buying, overpriced high IVol stocks should have larger absolute alphas than underpriced high IVol stocks. Hence, the relation between IVol and future returns will be negative overall.

Stambaugh et al. (2015) propose a comprehensive measure of mispricing, defined as the average rank of the firm from 11 independent sorts on priced firm characteristics, such as accruals, momentum, profitability, etc. Firms that are supposed to have the most positive alphas in each sort receive the highest ranking and vice versa, and the rankings are scaled to be between 0 and 1 and then averaged for all firms that are part of at least five sorts out of 11.

Panel A in Table 26A repeats Stambaugh et al. and finds that in the CAPM alphas, the IVol discount indeed exists only for the most overpriced firms, for which it reaches 1.55% per month, t-statistic 4.08. Consistent with Stambaugh et al. explanation, the driving force is the extremely negative alpha of high IVol overpriced firms, -1.39% per month, t-statistic -5.53.

Panel B presents the alphas from the volatility factor model with the market factor, FVIX, and FIVol, which handles well the IVol discount in the most overpriced subsample, reducing it from 1.55% to 0.345% per month and making it statistically insignificant. The volatility factors also significantly reduce the negative alpha of high IVol overpriced firms to -77.5 bp per month, t-statistic -3.20, and the difference in the IVol discount between overpriced and underpriced firms decreases from 1.54% to 0.97% per month.

On the other hand, the volatility factor model does little to explain the alpha spread created by the sorts on the Stambaugh et al. mispricing measure, which is the reason why we still observe a significantly negative alpha for high IVol overpriced stocks (which is now no longer different from the negative alpha of low IVol overpriced stocks). The volatility factor model also discovers flipped and significant IVol discount (positive alphas of high IVol firms) in the two underpriced quintiles, which would be more consistent with the conventional intuition (see, e.g., Merton, 1987, Boehme et al., 2009) that IVol, if anything, should be positively priced. While the positive pricing of IVol in the two underpriced quintiles can be consistent with both risk-based and mispricing explanations, it is beyond the scope of our paper.

Panel C and D present FVIX and FIVol betas of the double-sorted portfolios and find that, as previously, it is mainly FVIX that explains the IVol discount. The spread in FVIX betas between low and high IVol firms changes from -1.37 to -2.33 between the top underpricing and top overpricing quintiles, with t-statistic for the difference at -4.35.

Likewise, the FVIX beta of the high volatility overpriced firms is at 1.523, t-statistic 4.19, by far the largest FVIX beta in Panel C.

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A Data Appendix

AG (asset growth) – change in total assets (Compustat item at) from a year ago divided by total assets value from a year ago.

Amihud (Amihud illiquidity measure) – average ratio of absolute return to dollar volume, both from CRSP. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year or the stock price of less than $5 at the end of the previous year are excluded).

CAPF (capital ratio risk factor) – innovation from the AR(1) model fitted to equity capital ratio of primary dealers scaled by lagged equity capital ratio. The equity capital ratio is total market equity of all primary dealers as identified by New York Fed divided by the sum of total market equity plus total book value of debt of the said primary dealers. The variable is from the website of Zhiguo He at https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/

C-GARCH (Component GARCH) - following Adrian and Rosenberg (2008), we estimate

$$MKT_{t+1} - RF_{t+1} = \theta_1 + \theta_2 \cdot s_t + \theta_3 \cdot l_t + \sqrt{\nu_t} \cdot \epsilon_{t+1} \quad \text{(A7)}$$

$$\ln(\sqrt{\nu_t}) = s_t + l_t \quad \text{(A8)}$$

$$s_t = \theta_4 \cdot s_{t-1} + \theta_5 \cdot \epsilon_t + \theta_6 \cdot (|\epsilon_t| - \sqrt{2/\pi}) \quad \text{(A9)}$$

$$l_t = \theta_7 + \theta_8 \cdot l_{t-1} + \theta_9 \cdot \epsilon_t + \theta_{10} \cdot (|\epsilon_t| - \sqrt{2/\pi}) \quad \text{(A10)}$$

where s_t is the short-run (SR) volatility component and l_t is the long-run (LR) volatility component.

DEF (default spread) - defined as the yield spread between Moody's Baa and Aaa corporate bonds. The yields are obtained from the Federal Reserve Economic Data (FRED) database at https://fred.stlouisfed.org/.

DIV (dividend yield of the market index) - dividend yield of the CRSP market index, defined as the cumulative difference between its cum-dividend and ex-dividend return in the past 12 months.

FIVol (average idiosyncratic volatility risk factor – factor-mimicking portfolio that tracks monthly innovations to average idiosyncratic volatility, $\overline{IVOL}^U$. We regress $\overline{IVOL}^U$ on excess returns to five portfolios sorted on past sensitivity to $\overline{IVOL}^U$:

$$\overline{IVOL}^U_t = \gamma_0 + \gamma_1 \cdot (IS1_t - RF_t) + \gamma_2 \cdot (IS2_t - RF_t) + \\ + \gamma_3 \cdot (IS3_t - RF_t) + \gamma_4 \cdot (IS4_t - RF_t) + \gamma_5 \cdot (IS5_t - RF_t) \quad \text{(A11)}$$

where $IS1_t, \ldots, IS5_t$ are $\overline{IVOL}^U$ sensitivity quintiles described below, with $IS1_t$ being the quintile with the most negative sensitivity. The $\overline{IVOL}^U$ sensitivity quintiles in month t are formed using information from month t-1 and are rebalanced monthly.

The fitted part of the regression above less the constant is the FIVol factor:

$$FIVol_t = -1.39 \cdot (IS1_t - RF_t) - 1.95 \cdot (IS2_t - RF_t) - \\ -1.47 \cdot (IS3_t - RF_t) + 1.61 \cdot (IS4_t - RF_t) + 1.90 \cdot (IS5_t - RF_t) \tag{A12}$$

The return sensitivity to $\overline{IVOL}^U$ ($\beta_{\overline{IVOL}}$) we use to form the base assets is measured separately for each firm-month t by regressing, in months t-1 to t-60, monthly stock excess returns on monthly market excess returns and $\overline{IVOL}$ (at least 24 non-missing returns are required):

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{\overline{IVOL}} \cdot \overline{IVOL}_t^U \tag{A13}$$

FMAX (lottery demand factor) – the factor is the simple average between two strategies that go long in 30% of all firms with the lowest MAX and short in 30% of all firms with the highest MAX, separately for firms below NYSE market cap median and above that median. The returns of the two strategies are value-weighted. MAX is the average of the five highest daily returns in the past month (at least 15 non-missing daily returns are required).

FVIX (market volatility risk factor - factor-mimicking portfolio that tracks the daily changes in the VIX index. Following Ang, Hodrick, Xing, and Zhang (2006), we regress daily changes in VIX on daily excess returns to five portfolios sorted on past sensitivity to VIX changes:

$$\Delta VIX_t = \gamma_0 + \gamma_1 \cdot (VIX1_t - RF_t) + \gamma_2 \cdot (VIX2_t - RF_t) + \\ +\gamma_3 \cdot (VIX3_t - RF_t) + \gamma_4 \cdot (VIX4_t - RF_t) + \gamma_5 \cdot (VIX5_t - RF_t) \tag{A14}$$

where $VIX1_t, \ldots, VIX5_t$ are VIX sensitivity quintiles described below, with $VIX1_t$ being the quintile with the most negative sensitivity. The VIX sensitivity quintiles in month t are formed using information from month t-1 and are rebalanced monthly.

The fitted part of the regression above less the constant is the FVIX factor:

$$FVIX_t = -0.052 \cdot (VIX1_t - RF_t) - 0.611 \cdot (VIX2_t - RF_t) - \\ -0.378 \cdot (VIX3_t - RF_t) - 0.679 \cdot (VIX4_t - RF_t) + 0.194 \cdot (VIX5_t - RF_t) \tag{A15}$$

The daily returns to FVIX are then cumulated within each month to get the monthly return to FVIX.

The return sensitivity to VIX changes ($\beta_{\Delta VIX}$) we use to form the base assets is measured separately for each firm-month by regressing daily stock excess returns in the past month on daily market excess returns and the VIX index change (at least 15 non-missing returns are required):

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{\Delta VIX} \cdot \Delta VIX_t \tag{A16}$$

$\overline{\boldsymbol{IVOL}}^{\boldsymbol{U}}$ **(innovation to average idiosyncratic volatility)** – residual from ARMA(1,1) model fitted to average idiosyncratic volatility (see IVol below) averaged across all stocks in a particular month ($\overline{IVOL}^U$):

$$\overline{IVOL}_t = a + b \cdot \overline{IVOL}_{t-1} + c \cdot \overline{IVOL}^U_{t-1} + \overline{IVOL}^U_t \tag{A17}$$

$\boldsymbol{INT_{VW}}$ **(value-weighted equity return for the primary dealer sector)** – value-weighted return (from CRSP) of all primary dealers as identified by New York Fed. The variable is from the website of Zhiguo He at https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/

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.

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.

LEVold (original measure of leverage of securities broker-dealers) – total financial assets of securities broker-dealers divided by the difference between total financial assets and total liabilities of securities broker-dealers, as computed in Adrian et al. (2014) using aggregate quarterly data in Table L.129 of the Federal Reserve Flow of Funds. The variable is obtained from the website of Tyler Muir at https://sites.google.com/site/tylersmuir/home

LEVnew (newl measure of leverage of securities broker-dealers) – defined the same way as LEVold, but uses data from the new version of Federal Reserve Flow of Funds. The variable is obtained from the website of Tyler Muir listed above.

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.

MGMT factor – portfolio that goes long in the top and short in the bottom decile in the sorts on average rank of the firm from the sorts on five variables: distress, O-score, momentum, gross profitability, and return on assets (ROA). MGMT values are taken from the website of Robert Stambaugh at http://finance.wharton.upenn.edu/∼stambaug/

$\boldsymbol{\gamma_{PS}}$ **(Pastor-Stambaugh gamma)** - the firm return sensitivity to the firm previous-day dollar volume times the sign of the previous-day return, from

$$R_{t+1} = \theta + \phi R_t + \gamma_{PS} \cdot sign(R_t) \cdot Vol_t \tag{A18}$$

Both returns and dollar volume are from CRSP. The dollar volume is scaled by the ratio of current total market value of NYSE and AMEX shares to the total market value of NYSE and AMEX shares in January 1963.

$\boldsymbol{\Delta\gamma_{PS}}$ (**Pastor-Stambaugh (2003) non-traded factor**) – innovation to the market-wide monthly average (available from WRDS) of the Pastor-Stambaugh gamma, γ_{PS}.

$\boldsymbol{PS_{VW}}$ **(Pastor-Stambaugh (2003) traded factor)** – value-weighted return differential between top and bottom deciles (available from WRDS) from sorts on historical β_{PS}, the Pastor-Stambaugh beta wrt the non-traded factor described above. In each firm in month t, β_{PS} is estimated by running, for months t-1 to t-60, the regression below:

$$Ret_t - RF_t = \alpha + \beta_{MKT}(MKT_t - RF_t) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{PS} \cdot \Delta\gamma_{PS} \quad \text{(A19)}$$

PERF factor – portfolio that goes long in the top and short in the bottom decile in the sorts on average rank of the firm from the sorts on six variables: net issuance, cumulative issuance, accruals, net operating assets, asset growth, and investment-to-assets ratio.

PERF values are taken from the website of Robert Stambaugh at http://finance.wharton.upenn.edu/

Price – stock price (prc) from CRSP monthly returns file.

$\boldsymbol{PV_{Sadka}}$ **(Sadka (2006) permanent-variable non-traded factor)** – innovation to the market-wide average of the variable (information-based) price impact or Kyle's λ (available from WRDS).

PVGO (fraction of firm value coming from future growth) –

$$PVGO = 1 - \frac{E(CF)/MktCap}{WACC} \quad \text{(A20)}$$

E(CF) is the fitted part from fourth-order autoregression of quarterly cash flows. Cash flows are defined as net income minus accruals. Cash flows are operating income before depreciation (item oibdpq from Compustat quarterly file) 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. MktCap is shares outstanding times price, both from the CRSP monthly returns file. WACC assumes cost of equity for each firm to be equal to 6% plus the current risk-free rate, and the cost of debt to be 4% below cost of equity. Effective tax rate is computed as the ratio of total income tax (txt item in Compustat annual file) to pretax income (pi item).

Realized (realized market volatility) - the square root of the average squared daily return to the market portfolio (CRSP value-weighted index) within each given month.

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

$$log(\frac{Inst}{1 - Inst}) = \gamma_0 + \gamma_1 \cdot log(Size) + \gamma_2 \cdot log^2(Size) + \epsilon. \quad \text{(A21)}$$

Roll (Roll measure) - $\mathrm{Roll_t} = 200 \cdot \sqrt{-\mathrm{Cov}(R_t, R_{t-1})}$ if the covariance is positive and 0 otherwise.

Short (probability to be on special) - defined as in D'Avolio (2002) and Ali and Trombley (2006)

$$Short = \frac{e^y}{1 + e^y}, \quad \text{(A22)}$$

$$y = -0.46 \cdot log(Size) - 2.8 \cdot IO + 1.59 \cdot Turn - 0.09 \cdot \frac{CF}{TA} + 0.86 \cdot IPO + 0.41 \cdot Glam \quad \text{(A23)}$$

$Size$ is in million dollars, $Turn$ is turnover, defined as the trading volume over shares outstanding (from CRSP). CF is cash flow defined as Compustat item OIADP plus Compustat item DP) less non-depreciation accruals, which are change in current assets (Compustat item ACT) less change in current liabilities (Compustat item LCT) plus change in short-term debt (Compustat item DLC) less change in cash (Compustat item CHE). TA are total assets (Compustat item AT), IPO is the dummy variable equal to 1 if the stock first appeared on CRSP 12 or less months ago, and $Glam$ is the dummy variable equal to 1 for three top market-to-book deciles.

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

TARCH (expected market volatility) - from the TARCH(1,1) model (see Glosten, Jagannathan, and Runkle, 1993) fitted to monthly returns to the CRSP value-weighted index:

$$Ret_t^{CRSP} = \gamma_0 + \gamma_1 \cdot Ret_{t-1}^{CRSP} + \epsilon_t, \quad \sigma_t^2 = c_0 + c_1 \sigma_{t-1}^2 + c_2 \epsilon_{t-1}^2 + c_3 \cdot I(\epsilon_{t-1} < 0) \quad \text{(A24)}$$

The regression estimated for the full sample. We take the square root out of the volatility forecast to be consistent with our measure of idiosyncratic volatility.

TB (Treasury bill rate) - the 30-day T-bill rate from the FRED database at https://fred.stlouisfed.org/.

***TF**$_{Sadka}$* **(Sadka (2006) transitory-fixed non-traded factor)** – innovation to the market-wide average of the transitory (non-information-based) price impact (available from WRDS).

TED (TED spread) - the difference between the three-month LIBOR based in US dollarsand the three-month Treasury bill rate as reported by the FRED database at https://fred.stlouisfed.org/

TERM (term spread) - the yield spread between the ten-year and the one-year Treasury constant-maturity bond from the FRED database at https://fred.stlouisfed.org/.

TVol Sens - the sensitivity (γ) of firm's returns to changes in total firm-specific volatility, from firm-specific regressions of the form

$$Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \gamma \cdot \Delta Vol_t \quad \text{(A25)}$$

The regression is estimated using monthly data from months t-1 to t-60 (at least 24 valid observations are required). Volatility (Vol_t) is estimated separately each month by computing the standard deviation of daily returns (at least 15 non-missing returns are required).

VIX - the VIX index, defined as the implied volatility of at-the-money options

Table 1A. Robustness: Revisiting Bali and Cakici (2008)

In this table we look at equal-weighted Fama-French alphas of idiosyncratic volatility quintiles formed using NYSE only firms. Panel A uses the daily measure of idiosyncratic volatility, and Panel B uses the monthly measure. Idiosyncratic volatility is the standard deviation of Fama-French residuals. For the daily measure, in each firm-month with at least 15 valid observations we fit the model to daily returns. For the monthly measure, we fit the model to monthly returns over the previous 60 months (at least 24 valid observations required). We first classify firms as NYSE using the current listing, `hexcd` from the CRSP returns file, to mimic Bali and Cakici (2008). Then we add the delisting returns, and then use the listing at the portfolio formation date, `exchcd` from the CRSP events file. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2004.

Panel A. Daily Volatility, NYSE Only

	Low	IVol2	IVol3	IVol4	High	L-H
Raw$_{\texttt{hexcd}}$	1.162	1.404	1.539	1.614	1.415	-0.253
t-stat	*6.21*	*6.32*	*6.09*	*5.42*	*3.86*	*-1.08*
$\alpha_{\texttt{hexcd}}$	0.060	0.182	0.225	0.181	-0.260	0.319
t-stat	*0.86*	*2.49*	*2.62*	*1.95*	*-2.20*	*2.67*
$\alpha_{\texttt{+Delist}}$	0.063	0.183	0.227	0.182	-0.286	0.349
t-stat	*0.91*	*2.50*	*2.64*	*1.96*	*-2.42*	*2.91*
$\alpha_{\texttt{exchcd}}$	0.000	0.113	0.099	0.007	-0.850	0.849
t-stat	*-0.01*	*1.66*	*1.23*	*0.08*	*-6.89*	*6.30*

Panel B. Monthly Volatility, NYSE Only

	Low	IVol2	IVol3	IVol4	High	L-H
Raw$_{\texttt{hexcd}}$	1.164	1.324	1.435	1.467	1.672	-0.508
t-stat	*6.72*	*6.22*	*5.61*	*4.87*	*4.45*	*-1.87*
$\alpha_{\texttt{hexcd}}$	0.079	0.111	0.072	-0.001	0.045	0.034
t-stat	*1.14*	*1.58*	*0.86*	*-0.01*	*0.38*	*0.27*
$\alpha_{\texttt{+Delist}}$	0.080	0.112	0.076	-0.003	-0.057	0.137
t-stat	*1.16*	*1.60*	*0.91*	*-0.03*	*-0.47*	*1.07*
$\alpha_{\texttt{exchcd}}$	0.063	0.049	0.004	-0.134	-0.605	0.668
t-stat	*0.91*	*0.72*	*0.05*	*-1.44*	*-5.00*	*4.87*

Table 2A. Idiosyncratic Volatility Discount and Aggregate Volatility Risk in Event Time

The table reports the alphas and the FVIX betas, as well as raw returns, for the idiosyncratic volatility discount arbitrage portfolio (IVol), formed using the data on idiosyncratic volatility lagged by the number of months shown in the first row (one to twelve). For example, in column five we use idiosyncratic volatility measured five months ago to form idiosyncratic volatility quintiles and define the IVol arbitrage portfolio as the return differential between the lowest and the highest volatility quintiles. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The following models are used for measuring the alphas and betas: the CAPM, the Fama-French model, and the CAPM augmented with FVIX (2F). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The top two rows use the data from August 1963 to December 2008, the rest of the table looks at the sample period from January 1986 to December 2008.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1-12**
$\boldsymbol{\alpha}_{CAPM63}$	0.664	0.462	0.466	0.476	0.558	0.427	0.408	0.391	0.454	0.448	0.362	0.324	0.306
t-stat	*3.37*	*2.19*	*2.38*	*2.43*	*2.80*	*2.31*	*2.15*	*2.05*	*2.39*	*2.38*	*1.85*	*1.68*	*3.15*
$\boldsymbol{\alpha}_{FF63}$	0.672	0.398	0.426	0.468	0.573	0.423	0.471	0.430	0.493	0.487	0.404	0.368	0.299
t-stat	*4.73*	*3.09*	*3.20*	*3.49*	*4.23*	*3.32*	*3.42*	*3.12*	*3.54*	*3.88*	*3.23*	*2.96*	*3.08*
$\boldsymbol{\alpha}_{CAPM86}$	0.942	0.786	0.818	0.696	0.857	0.599	0.670	0.662	0.697	0.716	0.638	0.558	0.385
t-stat	*3.33*	*2.48*	*2.88*	*2.53*	*2.99*	*2.32*	*2.54*	*2.52*	*2.60*	*2.71*	*2.27*	*2.04*	*2.30*
$\boldsymbol{\alpha}_{FF86}$	0.696	0.363	0.506	0.426	0.638	0.332	0.488	0.447	0.487	0.493	0.420	0.324	0.373
t-stat	*3.07*	*1.74*	*2.54*	*2.13*	*3.07*	*1.75*	*2.33*	*2.21*	*2.25*	*2.63*	*2.28*	*1.78*	*2.25*
$\boldsymbol{\alpha}_{2F}$	0.330	0.217	0.190	0.097	0.290	0.052	0.152	0.085	0.224	0.161	0.097	0.022	0.308
t-stat	*1.77*	*1.07*	*0.97*	*0.53*	*1.45*	*0.27*	*0.75*	*0.41*	*1.06*	*0.88*	*0.46*	*0.10*	*1.92*
$\boldsymbol{\beta}_{FVIX}$	-1.787	-1.904	-1.834	-1.750	-1.656	-1.594	-1.512	-1.685	-1.378	-1.619	-1.579	-1.565	-0.222
t-stat	*-9.53*	*-10.55*	*-6.76*	*-7.93*	*-7.99*	*-6.60*	*-7.46*	*-7.95*	*-5.72*	*-7.78*	*-6.64*	*-6.97*	*-1.77*

Table 3A. Firm Characteristics across Double Sorts on Idiosyncratic Volatility and Market-to-Book/price-to-cash-flow

Panels A-F present median and average firm characteristics, as indicated in the panels' titles, across the five-by-five sorts on idiosyncratic volatility and market-to-book from Table 4A below. Panels G and H present median leverage and O-score across the five-by-five sorts on idiosyncratic volatility and price-to-cash-flow ratio from Table 3 in the paper. Idiosyncratic volatility is standard deviation of residuals from the Fama and French (1993) model, fitted to the daily data for each firm-month (at least 15 valid observations are required). Definitions of all other variables are in Data Appendix. The portfolios are sorted independently using NYSE (`exchcd`=1) breakpoints. The idiosyncratic volatility (market-to-book) portfolios are rebalanced monthly (annually). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Median Size

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	294.1	237.5	149.6	86.6	30.7	263.4	5.02
MB2	616.5	459.7	295.1	179.7	66.3	550.2	7.20
MB3	1131.5	758.1	447.7	252.5	83.8	1047.7	6.72
MB4	1819.7	1113.8	650.8	320.9	100.3	1719.4	7.83
Growth	3305.5	1906.8	887.7	414.2	127.4	3178.1	8.16
V-G	-3011.4	-1669.3	-738.1	-327.5	-96.8	-2914.6	8.31
t(V-G)	-8.35	-9.47	-9.43	-9.25	-7.57	8.31	

Panel B. Median Price

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	17.93	17.51	14.13	10.72	5.73	12.20	14.8
MB2	27.77	24.10	19.36	14.76	7.91	19.86	24.9
MB3	32.47	28.76	23.01	17.34	9.19	23.27	22.9
MB4	37.22	32.18	26.45	19.45	10.08	27.14	21.4
Growth	43.01	37.29	29.42	21.89	10.28	32.73	20.1
V-G	-25.08	-19.78	-15.29	-11.17	-4.55	20.53	20.0
t(V-G)	-20.7	-22.3	-20.8	-21.0	-11.0	20.0	

Panel C. Median Amihud (2002) Measure

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	1.063	0.542	0.718	1.141	4.841	-3.778	-6.67
MB2	0.236	0.211	0.315	0.583	2.426	-2.190	-5.81
MB3	0.129	0.124	0.192	0.339	1.458	-1.329	-6.20
MB4	0.104	0.099	0.139	0.263	1.062	-0.958	-5.35
Growth	0.070	0.038	0.066	0.135	0.575	-0.505	-8.15
V-G	0.993	0.504	0.652	1.006	4.267	3.273	6.29
t(V-G)	6.88	7.97	7.52	7.49	7.29	6.29	

Panel D. Median Roll (1984) Measure

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	1.062	1.170	1.353	1.645	2.824	-1.762	-14.0
MB2	0.983	1.105	1.261	1.501	2.410	-1.427	-14.7
MB3	0.968	1.079	1.240	1.482	2.291	-1.323	-17.6
MB4	0.973	1.080	1.253	1.513	2.221	-1.247	-20.2
Growth	1.027	1.145	1.343	1.651	2.364	-1.336	-24.9
V-G	0.034	0.025	0.010	-0.007	0.460	0.426	5.21
t(V-G)	1.21	0.93	0.38	-0.22	5.22	5.21	

Panel E. Average Return between months t-2 and t-12

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	11.31	11.61	11.48	12.91	11.60	-0.29	-0.13
MB2	12.77	12.40	13.02	14.10	12.46	0.30	0.14
MB3	13.62	14.07	14.53	15.92	14.77	-1.15	-0.46
MB4	15.01	15.86	16.99	17.58	15.12	-0.11	-0.04
Growth	16.36	19.31	21.13	23.98	23.47	-7.10	-2.03
V-G	-5.05	-7.70	-9.65	-11.15	-11.89	-6.83	-2.74
t(V-G)	-4.69	-6.07	-6.95	-6.11	-4.47	-2.74	

Panel F. Average Return in month t-1

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	-0.059	0.050	0.111	0.510	3.425	-3.484	-9.83
MB2	0.100	0.327	0.513	0.779	2.952	-2.853	-8.42
MB3	0.262	0.457	0.539	0.825	2.945	-2.683	-7.39
MB4	0.371	0.543	0.662	0.695	2.365	-1.994	-5.14
Growth	0.516	0.633	0.570	0.366	1.908	-1.391	-3.37
V-G	-0.575	-0.584	-0.459	0.143	1.517	2.092	8.51
t(V-G)	-6.50	-5.10	-3.30	0.88	5.96	8.51	

Panel G. Median Leverage

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	0.402	0.410	0.428	0.449	0.492	-0.090	-17.2
Quint2	0.270	0.279	0.282	0.281	0.287	-0.016	-2.33
Quint3	0.196	0.207	0.207	0.205	0.210	-0.014	-1.86
Quint4	0.133	0.136	0.136	0.132	0.146	-0.014	-1.86
Growth	0.073	0.068	0.065	0.062	0.074	-0.001	-0.18
V-G	0.330	0.342	0.363	0.387	0.418	0.089	
t(V-G)	37.6	44.7	48.0	50.3	55.0	13.1	

Panel H. Median O-Score

	Low	IVol2	IVol3	IVol4	High	L-H	t(L-H)
Value	-6.623	-6.620	-6.442	-6.206	-5.758	-0.865	-22.7
Quint2	-7.050	-6.989	-6.897	-6.732	-6.369	-0.681	-13.5
Quint3	-7.326	-7.259	-7.156	-7.020	-6.632	-0.694	-11.7
Quint4	-7.580	-7.556	-7.480	-7.334	-6.881	-0.699	-10.2
Growth	-7.678	-7.736	-7.641	-7.426	-6.755	-0.924	-9.85
V-G	1.056	1.116	1.199	1.220	0.997	-0.059	-0.71
t(V-G)	17.1	26.6	28.4	29.3	19.0		

Table 4A. Idiosyncratic Volatility and Market-to-Book

The table presents the value-weighted CAPM alphas (Panel A), alphas from the volatility factor model with the market factor, FVIX and FIVol (Panel B), and FVIX and FIVol betas from the volatility factor model (Panels C and D, respectively) for the 25 IVol - market-to-book portfolios. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The portfolios are sorted independently using NYSE (`exchcd`=1) breakpoints. The IVol (market-to-book) portfolios are rebalanced monthly (annually). The FVIX and FIVol betas estimates are from the volatility factor model with the market factor, FVIX and FIVol. FVIX (FIVol) is the aggregate (idiosyncratic) volatility risk factor that tracks innovations to VIX ($\overline{IVOL}$). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. CAPM Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	0.298	0.294	0.427	0.262	0.102	0.196
t-stat	*1.25*	*1.25*	*1.67*	*0.98*	*0.31*	*0.51*
MB2	0.311	0.301	0.260	0.438	-0.204	0.514
t-stat	*1.84*	*1.92*	*1.21*	*1.81*	*-0.94*	*1.89*
MB3	0.277	0.318	0.175	-0.092	-0.323	0.600
t-stat	*1.95*	*1.94*	*1.06*	*-0.54*	*-1.65*	*2.27*
MB4	0.441	0.326	-0.031	0.135	-0.473	0.914
t-stat	*3.05*	*2.48*	*-0.21*	*0.88*	*-2.23*	*3.25*
Growth	0.300	0.153	0.064	-0.220	-0.665	0.965
t-stat	*2.31*	*1.14*	*0.43*	*-1.16*	*-2.89*	*3.28*
V-G	-0.002	0.141	0.363	0.482	0.767	0.769
t(V-G)	*-0.01*	*0.50*	*1.18*	*1.37*	*2.14*	*2.20*

Panel B. Volatility Factor Model Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	-0.090	-0.119	0.152	0.133	0.017	-0.107
t-stat	*-0.43*	*-0.54*	*0.58*	*0.52*	*0.05*	*-0.27*
MB2	0.002	-0.016	-0.091	0.114	-0.031	0.033
t-stat	*0.01*	*-0.11*	*-0.50*	*0.59*	*-0.13*	*0.11*
MB3	-0.085	-0.044	-0.068	-0.315	-0.072	-0.012
t-stat	*-0.56*	*-0.22*	*-0.40*	*-1.82*	*-0.38*	*-0.05*
MB4	0.088	-0.068	-0.177	0.157	-0.099	0.187
t-stat	*0.68*	*-0.50*	*-1.16*	*1.05*	*-0.36*	*0.58*
Growth	0.130	0.025	0.183	0.084	0.121	0.009
t-stat	*1.08*	*0.16*	*1.08*	*0.48*	*0.47*	*0.03*
V-G	-0.220	-0.144	-0.032	0.049	-0.104	0.116
t(V-G)	*-0.86*	*-0.54*	*-0.10*	*0.15*	*-0.30*	*0.32*

Panel C. FVIX Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Value	-0.342	-0.262	0.127	0.649	0.749	-1.091
t-stat	*-1.57*	*-1.68*	*0.48*	*3.87*	*1.89*	*-1.93*
MB2	-0.433	-0.324	-0.148	0.090	0.937	-1.370
t-stat	*-4.31*	*-2.69*	*-0.83*	*0.33*	*3.72*	*-4.21*
MB3	-0.561	-0.488	-0.231	-0.036	0.905	-1.466
t-stat	*-4.73*	*-2.61*	*-1.38*	*-0.19*	*4.90*	*-5.87*
MB4	-0.722	-0.715	-0.140	0.271	0.989	-1.711
t-stat	*-5.04*	*-3.93*	*-0.74*	*2.08*	*3.06*	*-4.23*
Growth	-0.517	-0.351	0.192	0.542	1.586	-2.103
t-stat	*-2.76*	*-2.84*	*1.40*	*3.74*	*4.61*	*-4.52*
V-G	0.175	0.089	-0.065	0.107	-0.837	-1.012
t(V-G)	*0.86*	*0.59*	*-0.25*	*0.65*	*-2.94*	*-3.67*

Panel D. FIVol Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Value	-0.188	-0.240	-0.274	-0.352	-0.354	0.166
t-stat	*-3.89*	*-4.78*	*-5.66*	*-4.45*	*-3.56*	*1.50*
MB2	-0.089	-0.137	-0.232	-0.300	-0.214	0.125
t-stat	*-3.70*	*-5.07*	*-9.84*	*-8.73*	*-3.22*	*1.77*
MB3	-0.084	-0.112	-0.111	-0.169	-0.138	0.054
t-stat	*-3.08*	*-3.60*	*-3.86*	*-4.66*	*-5.13*	*1.30*
MB4	-0.015	-0.052	-0.067	-0.085	-0.069	0.054
t-stat	*-0.50*	*-2.14*	*-2.28*	*-3.89*	*-1.90*	*1.11*
Growth	0.057	0.028	0.025	0.044	0.042	0.014
t-stat	*1.99*	*1.43*	*0.95*	*1.45*	*0.99*	*0.23*
V-G	-0.245	-0.268	-0.299	-0.396	-0.397	-0.152
t(V-G)	*-5.55*	*-5.04*	*-4.95*	*-4.04*	*-3.82*	*-1.67*

Table 5A. Explaining the Idiosyncratic Volatility Effects

The table reports monthly alphas and betas of the HML factor and the four arbitrage portfolios (IVol, IVolh, HMLh, and IVol55) that measure the IVol discount and the value effect. IVol is the portfolio long in the lowest IVol quintile and short in the highest IVol quintile. IVolh is long in lowest IVol growth portfolio and short in highest IVol growth portfolio. HMLh is long in highest IVol value and short in highest IVol growth portfolio. IVol55 is long in high IVol growth portfolio and short in one-month Treasury bill. The asset-pricing models we fit to their returns are the CAPM, the three-factor Fama-French model (FF3), the Carhart model, the five-factor Fama-French model (FF5), the conditional CAPM (CCAPM), and the volatility factor model with the market factor, FVIX and FIVol. The FVIX and FIVol factors are defined in the heading of Table 3. In the conditional CAPM the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. Panel A and B report results for value- and equal-weighted returns, respectively. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Value-Weighted Returns

	α_{CAPM}	α_{FF3}	$\alpha_{Carhart}$	α_{FF5}	α_{CCAPM}	α_{VolF}	β_{FVIX}	β_{FIVol}
HML	0.310				0.244	-0.074	-0.429	-0.152
t-stat	*1.56*				*1.50*	*-0.40*	*-1.85*	*-5.05*
HMLh	0.767	0.369	0.641	0.265	0.707	-0.104	-0.837	-0.397
t-stat	*2.14*	*1.57*	*2.33*	*1.00*	*1.82*	*-0.30*	*-2.94*	*-3.82*
IVol	0.896	0.660	0.457	0.294	0.580	0.128	-1.915	0.097
t-stat	*3.51*	*4.88*	*3.25*	*2.46*	*2.40*	*0.51*	*-4.40*	*1.62*
IVolh	0.965	0.801	0.603	0.356	0.670	0.009	-2.103	0.014
t-stat	*3.28*	*4.16*	*3.17*	*1.87*	*2.48*	*0.03*	*-4.52*	*0.23*
IVol55	-0.665	-0.532	-0.416	-0.271	-0.442	0.121	1.586	0.042
t-stat	*-2.89*	*-3.84*	*-2.94*	*-2.04*	*-1.99*	*0.47*	*4.61*	*0.99*

Panel B. Equal-Weighted Returns

	α_{CAPM}	α_{FF3}	$\alpha_{Carhart}$	α_{FF5}	α_{CCAPM}	α_{VolF}	β_{FVIX}	β_{FIVol}
HMLh	1.092	0.703	0.723	0.417	0.922	0.303	-0.812	-0.339
t-stat	*3.64*	*4.35*	*5.41*	*3.37*	*3.57*	*1.09*	*-2.81*	*-6.82*
IVol	0.789	0.633	0.529	0.340	0.565	0.126	-1.409	-0.009
t-stat	*4.13*	*4.74*	*5.56*	*4.29*	*3.16*	*0.51*	*-4.05*	*-0.19*
IVolh	1.151	0.865	0.672	0.313	0.864	0.090	-2.082	-0.080
t-stat	*4.08*	*4.94*	*4.07*	*2.48*	*3.29*	*0.27*	*-3.70*	*-1.19*
IVol55	-0.888	-0.644	-0.534	-0.369	-0.729	-0.107	1.632	0.021
t-stat	*-3.87*	*-5.75*	*-4.76*	*-3.76*	*-3.11*	*-0.35*	*3.72*	*0.39*

Table 6A. Conditional CAPM Betas across Business Cycle

The table reports conditional CAPM betas across different states of the world for nine arbitrage portfolios. HML is the Fama-French factor. IVol is the portfolio long in the lowest volatility quintile and short in the highest volatility quintile. IVolh is long in lowest volatility growth portfolio and short in highest volatility growth portfolio. HMLh is long in highest volatility value and short in highest volatility growth portfolio. IVol55 is long in highest volatility growth portfolio and short in one-month Treasury bill. IVol IO (IVol Sh) is the portfolio long in the lowest volatility firms and short in the highest volatility firms within the lowest residual institutional ownership (highest probability to be on special) quintile. MB IO (MB Sh) is the portfolio long in the value firms and short in the growth firms within the lowest residual institutional ownership (highest probability to be on special) quintile. Recession (Expansion) is defined as the period when the expected market risk premium is higher (lower) than its in-sample mean. The expected risk premiums and the conditional betas are assumed to be linear functions of dividend yield, default spread, one-month Treasury bill rate, and term premium. The left part of the table presents the results with value-weighted returns, and the right part looks at equal-weighted returns. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2017.

	Value-Weighted			**Equal-Weighted**		
	β^{Rec}_{MKT}	β^{Exp}_{MKT}	$\beta^{Rec}_{MKT}-\beta^{Exp}_{MKT}$	β^{Rec}_{MKT}	β^{Exp}_{MKT}	$\beta^{Rec}_{MKT}-\beta^{Exp}_{MKT}$
HML	-0.032	-0.299	0.267			
t-stat	*-1.67*	*-18.0*	*10.1*			
IVol	-0.535	-0.796	0.260	-0.524	-0.772	0.248
t-stat	*-20.6*	*-29.0*	*6.57*	*-50.3*	*-47.1*	*11.8*
IVolh	-0.458	-0.844	0.386	-0.471	-0.872	0.401
t-stat	*-24.6*	*-29.3*	*10.6*	*-23.1*	*-27.8*	*10.1*
HMLh	0.035	-0.363	0.398	-0.165	-0.556	0.391
t-stat	*0.96*	*-13.4*	*8.37*	*-5.82*	*-19.4*	*9.25*
IVol55	1.368	1.666	-0.298	1.407	1.677	-0.270
t-stat	*128.9*	*90.9*	*-12.9*	*134.1*	*111.5*	*-13.5*
IVol IO	-0.467	-0.853	0.387	-0.434	-0.863	0.429
t-stat	*-10.4*	*-14.7*	*5.14*	*-12.5*	*-17.7*	*6.96*
IVol Sh	-0.167	-0.792	0.625	-0.300	-0.748	0.448
t-stat	*-2.63*	*-9.31*	*5.79*	*-7.19*	*-13.4*	*6.31*
HML IO	-0.421	-0.876	0.455	0.301	-0.362	0.663
t-stat	*-13.4*	*-18.9*	*7.87*	*7.58*	*-6.67*	*9.43*
HML Sh	0.250	-0.484	0.734	-0.010	-0.480	0.470
t-stat	*6.20*	*-8.67*	*10.1*	*-0.33*	*-17.1*	*10.8*

Table 7A. Conditioning Variables vs. Aggregate Volatility Risk Factors

The table reports the alphas, FVIX betas, and FIVol betas of the nine arbitrage portfolios described in the heading of Table 6A. The models fitted to returns of the arbitrage assets are the CAPM, the Conditional CAPM, the volatility factor model with the market factor, FVIX, and FIVol (VolF), and the Conditional CAPM augmented with FVIX and FIVol (C-VolF). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2017.

	α_{CAPM}	α_{CCAPM}	α_{VolF}	β_{FVIX}	β_{FIVol}	α_{C-VolF}	β_{FVIX}	β_{FIVol}
HML	0.311	0.245	-0.074	-0.429	-0.152	-0.028	-0.472	-0.081
t-stat	*1.57*	*1.51*	*-0.40*	*-1.85*	*-5.05*	*-0.16*	*-2.37*	*-2.30*
IVol	0.788	0.564	0.126	-1.409	-0.009	0.090	-1.292	0.051
t-stat	*4.14*	*3.16*	*0.51*	*-4.05*	*-0.19*	*0.39*	*-3.79*	*1.18*
IVolh	1.145	0.856	0.090	-2.082	-0.080	0.084	-1.944	0.010
t-stat	*4.07*	*3.28*	*0.27*	*-3.70*	*-1.19*	*0.26*	*-3.55*	*0.17*
HMLh	1.086	0.916	0.303	-0.812	-0.339	0.344	-0.846	-0.237
t-stat	*3.62*	*3.55*	*1.09*	*-2.81*	*-6.82*	*1.26*	*-3.23*	*-5.05*
IVol55	-0.882	-0.722	-0.107	1.632	0.021	-0.129	1.607	-0.054
t-stat	*-3.85*	*-3.09*	*-0.35*	*3.72*	*0.39*	*-0.44*	*3.76*	*-1.04*
IVol IO	1.197	0.969	0.330	-1.749	-0.042	0.323	-1.638	0.026
t-stat	*4.57*	*3.95*	*0.94*	*-3.78*	*-0.71*	*0.97*	*-3.63*	*0.47*
IVol Sh	1.092	0.859	0.245	-1.631	-0.079	0.245	-1.489	-0.015
t-stat	*4.31*	*3.65*	*0.74*	*-3.68*	*-1.29*	*0.78*	*-3.43*	*-0.26*
HML IO	0.831	0.587	-0.099	-0.957	-0.407	-0.069	-0.879	-0.313
t-stat	*2.41*	*2.08*	*-0.32*	*-2.64*	*-6.16*	*-0.23*	*-2.33*	*-5.60*
HML Sh	1.140	1.037	0.233	-0.815	-0.442	0.315	-0.871	-0.384
t-stat	*3.34*	*3.24*	*0.72*	*-2.29*	*-6.01*	*0.98*	*-2.47*	*-4.64*

Table 8A. Alternative Specifications of FVIX and FIVol

Panel A presents correlations between monthly change in VIX (Δ VIX) and three versions of the FVIX factor - the one used in the paper (FVIX), the one from factor-mimicking regression estimated using expanding window (FVIXT), and the one from factor-mimicking regression estimated using one-month rolling window, as in Ang et al. (FVIXO). Panel B reports correlations between two versions of innovation to average idiosyncratic volatility: $\overline{IVOL}^U$ (residual from full-sample ARMA(1,1) model fitted to average volatility, used in the paper) and $\overline{IVOL}_T^U$ (residual from expanding-window ARMA(1,1), fitted using only the available data and forecasted one period ahead, i.e., out of sample), as well as three versions of FIVol: FIVol (mimics $\overline{IVOL}^U$ using a full-sample factor-mimicking regression, used in the paper), FIVolT (mimics $\overline{IVOL}^U$ using an expanding-window factor-mimicking regression), and FIVolTT (mimics $\overline{IVOL}_T^U$ using an expanding-window factor-mimicking regression). Panel C reports descriptive statistics of FVIX and FIVol versions along with those of standard asset-pricing factors. Panels D-G present alphas and betas of alternative FVIX and FIVol versions. The alphas and betas are from the CAPM, the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the FF5 model augmented with the Carhart's momentum factor (the FF6 model). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2017.

Panel A. Correlations: FVIX Versions

	Δ VIX	**FVIX**	**FVIXT**	**FVIXO**
Δ VIX	1	0.731	0.738	0.607
FVIX	0.731	1	0.991	0.768
FVIXT	0.738	0.991	1	0.779
FVIXO	0.607	0.768	0.779	1

Panel B. Correlations: FIVol Versions

	$\overline{IVOL}^U$	$\overline{IVOL}_T^U$	**FIVol**	**FIVolT**	**FIVolTT**
$\overline{IVOL}^U$	1	0.998	0.424	0.323	0.360
$\overline{IVOL}_T^U$	0.998	1	0.429	0.329	0.364
FIVol	0.424	0.429	1	0.927	0.938
FIVolT	0.323	0.329	0.927	1	0.944
FIVolTT	0.360	0.364	0.938	0.944	1

Panel C. Factors Descriptive Statistics

	Mean	StDev	Sharpe	α_{CAPM}	Appraisal
MKT	0.682	4.391	0.155		
SMB	0.086	3.006	0.029	-0.005	-0.002
HML	0.215	2.920	0.074	0.310	0.109
MOM	0.515	4.589	0.112	0.645	0.143
FVIX	-1.366	5.978	-0.229	-0.463	-0.337
FVIXT	-1.143	4.518	-0.253	-0.381	-0.398
FVIXO	-0.933	7.087	-0.132	-0.253	-0.046
FIVOL	-1.943	7.951	-0.244	-1.220	-0.189
FIVOLT	-1.550	7.138	-0.217	-0.970	-0.159
FIVOLTT	-2.416	11.399	-0.212	-1.352	-0.148

Panel D. Tradable FVIX (aka FVIXT)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.143	-0.381	-0.381	-0.404	-0.295	-0.317
t-stat	*-4.71*	*-4.66*	*-4.29*	*-4.34*	*-3.97*	*-4.16*
$\boldsymbol{\beta}_{MKT}$		-1.059	-1.073	-1.063	-1.114	-1.105
t-stat		*-34.8*	*-33.9*	*-31.7*	*-43.0*	-41.1
$\boldsymbol{\beta}_{SMB}$			0.077	0.074	0.036	0.031
t-stat			*3.12*	*3.40*	*1.90*	*1.68*
$\boldsymbol{\beta}_{HML}$			-0.028	-0.017	0.043	0.067
t-stat			*-0.79*	*-0.51*	*1.08*	*1.62*
$\boldsymbol{\beta}_{MOM}$				0.029		0.038
t-stat				*1.80*		*2.23*
$\boldsymbol{\beta}_{CMA}$					-0.082	-0.098
t-stat					*-1.66*	*-2.18*
$\boldsymbol{\beta}_{RMW}$					-0.138	-0.147
t-stat					*-4.60*	*-5.02*

Panel E. Ang et al.'s FVIX (aka FVIXO)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-0.933	-0.253	-0.220	-0.216	0.025	0.010
t-stat	*-2.97*	*-0.96*	*-0.91*	*-0.84*	*0.09*	*0.03*
$\boldsymbol{\beta}_{MKT}$		-1.023	-1.050	-1.052	-1.137	-1.132
t-stat		*-9.59*	*-10.1*	*-9.52*	*-8.86*	*-8.73*
$\boldsymbol{\beta}_{SMB}$			0.095	0.096	-0.044	-0.047
t-stat			*0.77*	*0.76*	*-0.38*	*-0.40*
$\boldsymbol{\beta}_{HML}$			-0.105	-0.108	0.063	0.084
t-stat			*-0.71*	*-0.75*	*0.30*	*0.38*
$\boldsymbol{\beta}_{MOM}$				-0.006		0.030
t-stat				*-0.11*		*0.45*
$\boldsymbol{\beta}_{CMA}$					-0.169	-0.184
t-stat					*-0.64*	*-0.68*
$\boldsymbol{\beta}_{RMW}$					-0.467	-0.476
t-stat					*-2.04*	*-2.02*

Panel F. FIVolT with Full-Sample ARMA(1,1)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.543	-0.962	-0.736	-1.097	-0.788	-1.041
t-stat	*-3.18*	*-2.22*	*-2.09*	*-2.92*	*-2.02*	*-2.69*
$\boldsymbol{\beta}_{MKT}$		-0.851	-0.861	-0.744	-0.843	-0.770
t-stat		*-4.67*	*-6.01*	*-5.84*	*-5.42*	*-5.56*
$\boldsymbol{\beta}_{SMB}$			-0.694	-0.715	-0.664	-0.716
t-stat			*-5.67*	*-8.38*	*-5.43*	*-7.23*
$\boldsymbol{\beta}_{HML}$			-0.732	-0.547	-0.768	-0.452
t-stat			*-5.18*	*-4.36*	*-3.92*	*-3.09*
$\boldsymbol{\beta}_{MOM}$				0.467		0.479
t-stat				*3.83*		*3.98*
$\boldsymbol{\beta}_{CMA}$					0.036	-0.196
t-stat					*0.14*	*-0.95*
$\boldsymbol{\beta}_{RMW}$					0.100	-0.039
t-stat					*0.56*	*-0.25*

Panel G. FIVolTT with Expanding-Window ARMA(1,1)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-2.406	-1.342	-0.971	-1.449	-0.944	-1.285
t-stat	*-3.19*	*-2.07*	*-1.90*	*-2.69*	*-1.66*	*-2.32*
$\boldsymbol{\beta}_{MKT}$		-1.561	-1.606	-1.451	-1.611	-1.513
t-stat		*-6.26*	*-8.70*	*-8.60*	*-7.81*	*-8.16*
$\boldsymbol{\beta}_{SMB}$			-0.918	-0.945	-0.964	-1.035
t-stat			*-3.93*	*-5.39*	*-4.90*	*-6.24*
$\boldsymbol{\beta}_{HML}$			-1.200	-0.956	-1.220	-0.794
t-stat			*-5.59*	*-5.06*	*-4.44*	*-3.75*
$\boldsymbol{\beta}_{MOM}$				0.618		0.646
t-stat				*3.52*		*3.86*
$\boldsymbol{\beta}_{CMA}$					0.110	-0.204
t-stat					*0.27*	*-0.64*
$\boldsymbol{\beta}_{RMW}$					-0.127	-0.314
t-stat					*-0.50*	*-1.47*

Table 9A. Alternative FVIX/FIVol Factors and the Anomalies

The table uses the three FVIX specifications and the three FIVol specifications from Table 8A to explain the alphas of the long-short portfolios from Table 5A. HML is the Fama-French value-minus-growth factor. IVol is the portfolio long in the lowest IVol quintile and short in the highest IVol quintile. IVolh is long in lowest IVol growth portfolio and short in highest IVol growth portfolio. HMLh is long in highest IVol value and short in highest IVol growth portfolio. IVol55 is long in high IVol growth portfolio and short in one-month Treasury bill. Panel A adds the alternative FVIX factors to the two-factor model with the market factor and FVIX (2F). Panel B adds the alternative FVIX factors to the volatility factor model with the market factor, FVIX, and FIVol (VolF). Panel C uses the alternative FIVol factors along with FVIXT in the volatility factor model.

Panel A. Alternative FVIX Factors in Two-Factor Model

	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{2F}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\alpha}_{2F-T}$	$\boldsymbol{\beta}_{FVIXT}$	$\boldsymbol{\alpha}_{2F-O}$	$\boldsymbol{\beta}_{FVIXO}$
HML	0.311	0.133	-0.383	0.208	-0.337	0.303	-0.031
t-stat	*1.57*	*0.70*	*-1.25*	*0.88*	*-0.75*	*1.56*	*-0.65*
HMLh	0.756	0.435	-0.716	0.180	-1.614	0.769	-0.042
t-stat	*2.11*	*1.12*	*-2.57*	*0.43*	*-3.29*	*2.15*	*-0.72*
IVol	0.896	-0.004	-1.945	0.085	-2.022	0.854	-0.115
t-stat	*3.52*	*-0.02*	*-4.96*	*0.26*	*-2.92*	*3.49*	*-1.75*
IVolh	0.958	-0.010	-2.107	-0.013	-2.332	0.924	-0.115
t-stat	*3.26*	*-0.04*	*-4.58*	*-0.03*	*-2.89*	*3.24*	*-1.45*
IVol55	-0.664	0.063	1.573	0.114	1.852	-0.636	0.062
t-stat	*-2.90*	*0.26*	*4.42*	*0.32*	*3.02*	*-2.78*	*1.13*

Panel B. Alternative FVIX Factors in Volatility Factor Model

	α_{VolF}	β_{FVIX}	β_{FIVol}	α_{VolF-T}	β_{FVIXT}	β_{FIVol}	α_{VolF-O}	β_{FVIXO}	β_{FIVol}
HML	-0.074	-0.429	-0.152	-0.018	-0.366	-0.155	0.127	-0.021	-0.146
t-stat	*-0.40*	*-1.85*	*-5.05*	*-0.08*	*-1.10*	*-4.51*	*0.75*	*-0.64*	*-4.26*
HMLh	-0.104	-0.837	-0.397	-0.406	-1.690	-0.401	0.304	-0.017	-0.383
t-stat	*-0.30*	*-2.94*	*-3.82*	*-1.01*	*-3.54*	*-4.01*	*0.86*	*-0.35*	*-3.42*
IVol	0.128	-1.915	0.097	0.226	-2.004	0.096	1.010	-0.124	0.128
t-stat	*0.51*	*-4.40*	*1.62*	*0.64*	*-2.66*	*1.37*	*4.42*	*-1.67*	*1.60*
IVolh	0.009	-2.103	0.014	0.004	-2.330	0.012	0.981	-0.118	0.047
t-stat	*0.03*	*-4.52*	*0.23*	*0.01*	*-2.86*	*0.17*	*3.59*	*-1.46*	*0.59*
IVol55	0.121	1.586	0.042	0.181	1.860	0.046	-0.613	0.060	0.019
t-stat	*0.47*	*4.61*	*0.99*	*0.50*	*3.13*	*0.97*	*-2.66*	*1.17*	*0.32*

Panel C. Alternative FIVol Factors in Three-Factor ICAPM

	α_{VolF}	β_{FVIX}	β_{FIVol}	α_{VolF-T}	β_{FVIXT}	β_{FIVolT}	$\alpha_{VolF-TT}$	β_{FVIXTT}	$\beta_{FIVolTT}$
HML	-0.074	-0.429	-0.152	-0.003	-0.423	-0.164	0.010	-0.375	-0.120
t-stat	*-0.40*	*-1.85*	*-5.05*	*-0.01*	*-1.20*	*-4.84*	*0.04*	*-1.15*	*-5.16*
HMLh	-0.104	-0.837	-0.397	-0.427	-1.864	-0.472	-0.325	-1.713	-0.306
t-stat	*-0.30*	*-2.94*	*-3.82*	*-1.06*	*-4.02*	*-4.60*	*-0.84*	*-3.73*	*-4.53*
IVol	0.128	-1.915	0.097	0.325	-1.924	0.187	0.239	-1.992	0.093
t-stat	*0.51*	*-4.40*	*1.62*	*0.95*	*-2.44*	*2.48*	*0.67*	*-2.56*	*1.71*
IVolh	0.009	-2.103	0.014	0.082	-2.293	0.074	0.019	-2.326	0.019
t-stat	*0.03*	*-4.52*	*0.23*	*0.20*	*-2.73*	*1.00*	*0.05*	*-2.82*	*0.37*
IVol55	0.121	1.586	0.042	0.122	1.855	0.006	0.165	1.862	0.031
t-stat	*0.47*	*4.61*	*0.99*	*0.33*	*3.03*	*0.13*	*0.45*	*3.12*	*0.87*

Table 10A. Alternative Measures of Volatility Risk

The table presents the alphas (Panel A) and aggregate volatility risk betas (Panels B and C) from the following eight models:

$$Model\,0 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) \tag{A26}$$

$$Model\,1 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \tag{A27}$$

$$Model\,2 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t \tag{A28}$$

$$Model\,3 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FIVol} \cdot FIVol_t \tag{A29}$$

$$Model\,4 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FVIX} \cdot FVIX_t \tag{A30}$$

$$Model\,5 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \tag{A31}$$

$$Model\,6 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{AV} \cdot AV_t \tag{A32}$$

$$Model\,7 \;:\; Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{AV} \cdot AV_t + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \tag{A33}$$

The volatility risk factors are FVIX (the factor-mimicking portfolio tracking the changes in VIX), FIVol (the factor-mimicking portfolio tracking innovations to average idiosyncratic volatility), factor-mimicking portfolios for the short-run (SR) and long-run (LR) market volatility components from the C-GARCH model in Adrian and Rosenberg (2008), and the average volatility factor (AV) from Chen and Petkova (2012). The base assets for the SR, LR, AV factors are quintile portfolios sorted on the sensitivity to the innovations in the past 36 months.

The test assets on the left-hand side of the equations above are reported in the leftmost column of each panel. HML is the Fama-French factor. IVol is the portfolio long in the lowest volatility quintile and short in the highest volatility quintile. IVolh is long in lowest volatility growth portfolio and short in highest volatility growth portfolio. HMLh is long in highest volatility value and short in highest volatility growth portfolio. IVol55 is long in highest volatility growth portfolio and short in one-month Treasury bill. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from August 1963 to December 2017.

Panel A. Alphas from Competing Models

	0	1	2	3	4	5	6	7
HML	0.310	-0.074	0.197	0.034	0.182	-0.004	0.229	-0.077
t-stat	*1.56*	*-0.40*	*1.10*	*0.20*	*1.08*	*-0.02*	*1.26*	*-0.42*
IVol	0.896	0.128	0.532	0.669	0.129	0.263	0.921	0.056
t-stat	*3.51*	*0.51*	*2.70*	*3.55*	*0.70*	*1.51*	*3.57*	*0.22*
IVolh	0.965	0.009	0.575	0.615	0.130	0.152	0.941	-0.069
t-stat	*3.28*	*0.03*	*2.39*	*2.49*	*0.54*	*0.61*	*3.20*	*-0.23*
HMLh	0.767	-0.104	0.718	0.229	0.430	-0.141	0.548	-0.138
t-stat	*2.14*	*-0.30*	*1.92*	*0.62*	*1.14*	*-0.40*	*1.56*	*-0.39*
IVol55	-0.665	0.121	-0.379	-0.350	-0.038	0.014	-0.615	0.175
t-stat	*-2.89*	*0.47*	*-1.88*	*-1.70*	*-0.18*	*0.07*	*-2.63*	*0.68*

Panel B. Volatility Risk Betas: Traded Alternative Factors

	1		**2**				**5**		**6**	**7**		
	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{FIVol}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{FIVol}$	$\boldsymbol{\beta}_{AV}$	$\boldsymbol{\beta}_{AV}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{FIVol}$
HML	-0.429	-0.152	-0.001	-0.203	0.003	-0.163	-0.093	-0.136	-0.035	-0.022	-0.472	-0.090
t-stat	*-1.85*	*-5.05*	*-0.39*	*-4.74*	*0.74*	*-4.39*	*-0.50*	*-5.00*	*-3.86*	*-2.22*	*-1.93*	*-2.45*
IVol	-1.548	0.083	0.025	-0.397	0.018	-0.350	-0.692	0.093	0.023	-0.001	-1.558	0.072
t-stat	*-4.17*	*1.62*	*5.86*	*-9.20*	*3.96*	*-5.99*	*-2.80*	*2.38*	*1.21*	*-0.04*	*-4.15*	*0.96*
IVolh	-2.103	0.014	0.030	-0.483	0.024	-0.375	-1.139	0.016	0.008	-0.013	-2.147	0.032
t-stat	*-4.52*	*0.23*	*5.45*	*-7.95*	*3.83*	*-5.08*	*-3.25*	*0.33*	*0.31*	*-0.51*	*-4.57*	*0.43*
HMLh	-0.837	-0.397	-0.005	-0.116	0.005	0.069	-0.909	-0.417	-0.089	-0.047	-0.942	-0.266
t-stat	*-2.94*	*-3.82*	*-0.64*	*-1.12*	*0.55*	*0.82*	*-3.12*	*-3.71*	*-3.08*	*-1.90*	*-3.47*	*-2.42*
IVol55	1.586	0.042	-0.019	0.372	-0.016	0.277	0.894	0.038	0.010	0.023	1.643	-0.005
t-stat	*4.61*	*0.99*	*-4.20*	*7.60*	*-3.21*	*6.09*	*3.85*	*1.06*	*0.57*	*1.15*	*4.71*	*-0.10*

Table 11A. Volatility Risk Factors for a Longer Sample

The table uses a longer sample, January 1963 to December 2017. Panel A uses factor-mimicking portfolios for changes in short-run (SR) and long-run (LR) volatility forecasts estimated using Component GARCH model, as in Adrian and Rosenberg (2008) to explain the returns to the long-short portfolios from Table 5A. Panel A adds the SR and LR factors to the CAPM (the Adrian-Rosenberg, AR, model) and to the two-factor model with FIVol (AR4L). Panel B uses the baseline FVIX (base assets - quintile portfolios pre-sorted on historical sensitivity to VIX changes), and FVIX63, the FVIX factor backfilled to cover 1963-2017 (base assets - Fama-French two-by-three size-BM sorts) to explain the alphas of the same long-short portfolios. The market factor is present in all models in the table, but the market betas of the long-short portfolios are not reported for brevity.

Panel A. Long-Run/Short-Run Volatility Factors in 1963-2017

	CAPM	**AR model**			**AR4L model**			
	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{AR}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\alpha}_{AR4L}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\beta}_{FIVol}$
HML	0.434	0.240	-0.208	-0.004	0.101	-0.186	0.000	-0.144
t-stat	*3.21*	*1.97*	*-7.56*	*-1.73*	*0.84*	*-8.32*	*-0.11*	*-6.21*
HMLh	0.927	0.811	-0.196	-0.015	0.349	-0.144	-0.003	-0.370
t-stat	*3.54*	*2.95*	*-2.89*	*-2.38*	*1.30*	*-2.24*	*-0.50*	*-3.84*
IVol	0.665	0.191	-0.324	0.032	0.427	-0.339	0.027	0.143
t-stat	*3.48*	*1.16*	*-5.09*	*8.15*	*2.66*	*-5.10*	*6.75*	*2.64*
IVolh	0.890	0.412	-0.429	0.033	0.504	-0.431	0.033	0.040
t-stat	*3.77*	*2.03*	*-4.85*	*8.28*	*2.40*	*-5.09*	*7.80*	*0.72*
IVol55	-0.743	-0.418	0.371	-0.034	-0.585	0.380	-0.032	-0.085
t-stat	*-4.04*	*-2.05*	*5.68*	*-8.30*	*-2.77*	*5.89*	*-7.09*	*-1.61*

Panel B. Backfilled FVIX

	CAPM	Baseline FVIX			FVIX63, 1986-2017			FVIX63, 1963-2017			
	$\boldsymbol{\alpha}_{CAPM86}$	$\boldsymbol{\alpha}_{VolF}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{FIVol}$	$\boldsymbol{\alpha}_{VolF}$	$\boldsymbol{\beta}_{FVIX63}$	$\boldsymbol{\beta}_{FIVol}$	$\boldsymbol{\alpha}_{CAPM63}$	$\boldsymbol{\alpha}_{VolF}$	$\boldsymbol{\beta}_{FVIX63}$	$\boldsymbol{\beta}_{FIVol}$
HML	0.311	-0.074	-0.429	-0.152	-0.028	-0.468	-0.143	0.434	0.174	-0.283	-0.179
t-stat	*1.57*	*-0.40*	*-1.85*	*-5.05*	*-0.16*	*-2.69*	*-5.13*	*3.21*	*1.30*	*-1.71*	*-6.76*
HMLh	0.756	-0.104	-0.837	-0.397	0.138	-0.443	-0.383	0.927	0.388	-0.261	-0.405
t-stat	*2.11*	*-0.30*	*-2.94*	*-3.82*	*0.41*	*-2.19*	*-3.54*	*3.54*	*1.49*	*-1.37*	*-4.83*
IVol	0.896	0.128	-1.915	0.097	0.231	-1.730	0.188	0.665	0.403	-1.766	0.151
t-stat	*3.52*	*0.51*	*-4.40*	*1.62*	*1.01*	*-6.71*	*3.16*	*3.48*	*2.40*	*-8.62*	*2.85*
IVolh	0.958	0.009	-2.103	0.014	0.088	-2.405	0.077	0.890	0.454	-2.324	0.046
t-stat	*3.26*	*0.03*	*-4.52*	*0.23*	*0.32*	*-6.68*	*1.26*	*3.77*	*2.20*	*-7.81*	*0.90*
IVol55	-0.664	0.121	1.586	0.042	-0.193	2.191	-0.137	-0.743	-0.508	2.257	-0.096
t-stat	*-2.90*	*0.47*	*4.61*	*0.99*	*-0.75*	*7.88*	*-2.61*	*-4.04*	*-2.50*	*9.76*	*-1.94*

Panel C. Backfilled FVIX and Double Sorts on Price-to-Cash-Flow and IVol

Panel C1. Value-Weighted Returns

	$\boldsymbol{\alpha}_{CAPM63}$	$\boldsymbol{\alpha}_{ICAPM63}$	$\boldsymbol{\beta}_{FVIX63}$	$\boldsymbol{\alpha}_{VolF}$	$\boldsymbol{\beta}_{FVIX63}$	$\boldsymbol{\beta}_{FIVol}$
VMG	0.507	0.452	-0.272	0.133	-0.309	-0.258
t-stat	*2.88*	*2.50*	*-1.13*	*0.88*	*-1.95*	*-8.32*
IVol	0.634	0.277	-1.758	0.380	-1.745	0.084
t-stat	*3.54*	*1.99*	*-11.1*	*2.77*	*-9.91*	*2.31*
IVolG	0.793	0.441	-1.733	0.513	-1.724	0.058
t-stat	*3.45*	*2.24*	*-9.04*	*2.59*	*-9.21*	*1.35*
VMGh	0.863	0.731	-0.651	0.372	-0.693	-0.289
t-stat	*3.20*	*2.85*	*-2.60*	*1.56*	*-3.72*	*-6.10*
IVol51	-0.689	-0.460	1.127	-0.471	1.125	-0.009
t-stat	*-4.12*	*-2.99*	*6.81*	*-3.03*	*6.81*	*-0.21*

Panel C2. Equal-Weighted Returns

	$\boldsymbol{\alpha}_{CAPM63}$	$\boldsymbol{\alpha}_{ICAPM63}$	$\boldsymbol{\beta}_{FVIX63}$	$\boldsymbol{\alpha}_{VolF}$	$\boldsymbol{\beta}_{FVIX63}$	
VMG	0.901	0.802	-0.489	0.478	-0.527	-0.262
t-stat	*5.41*	*4.62*	*-2.00*	*3.14*	*-3.40*	*-9.65*
IVol	0.676	0.070	-1.732	0.251	-1.711	0.146
t-stat	*4.42*	*0.39*	*-9.29*	*1.46*	*-8.06*	*2.83*
IVolG	0.732	0.127	-1.695	0.249	-1.681	0.098
t-stat	*4.27*	*0.76*	*-9.36*	*1.55*	*-8.77*	*2.31*
VMGh	0.944	0.802	-0.697	0.463	-0.737	-0.274
t-stat	*5.13*	*4.23*	*-2.69*	*2.63*	*-4.22*	*-7.90*
IVol51	-0.742	-0.106	1.815	-0.298	1.792	-0.156
t-stat	*-4.85*	*-0.62*	*9.30*	*-1.84*	*10.0*	*-3.55*

Table 12A. RMW factor and Aggregate Volatility Risk

Panel A presents the estimates of factor models fitted to returns to the RMW factor of Fama and French (2015). RMW buys (shorts) firms in the top 30% (bottom 30%) on profitability. The returns to the strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large firms, and then averaged. The sorts on profitability are independent of size and use NYSE breakpoints. Panel B presents the estimates of factor models fitted to return to FVIX. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. RMW on FVIX

	Raw	CAPM	2F	FF	FF4	Carhart	FF5
α	0.351	0.496	0.116	0.431	0.176	0.386	0.126
t-stat	*2.43*	*3.55*	*0.70*	*3.28*	*1.42*	*3.03*	*1.06*
β_{MKT}		-0.213	-1.319	-0.141	-0.947	-0.127	-0.938
t-stat		*-4.23*	*-3.68*	*-2.94*	*-5.02*	*-3.07*	*-4.88*
β_{SMB}				-0.320	-0.218	-0.322	-0.220
t-stat				*-3.12*	*-2.63*	*-3.00*	*-2.54*
β_{HML}				0.208	0.166	0.231	0.190
t-stat				*2.10*	*2.04*	*2.47*	*2.44*
β_{MOM}						0.058	0.062
t-stat						*1.09*	*1.29*
β_{FVIX}			-0.835		-0.593		-0.598
t-stat			*-3.23*		*-4.37*		*-4.34*

Panel B. FVIX on RMW

	Raw	CAPM	FF	+RMW	+CMA	Carhart	+RMW	+CMA
α	-1.366	-0.463	-0.439	-0.347	-0.305	-0.444	-0.359	-0.319
t-stat	*-4.77*	*-4.73*	*-4.00*	*-3.72*	*-3.73*	*-3.91*	*-3.75*	*-3.80*
β_{MKT}		-1.325	-1.358	-1.388	-1.407	-1.357	-1.384	-1.403
t-stat		*-37.0*	*-35.2*	*-41.7*	*-50.7*	*-34.0*	*-40.3*	*-49.2*
β_{SMB}			0.170	0.103	0.107	0.170	0.100	0.104
t-stat			*4.94*	*4.43*	*4.56*	*5.08*	*4.48*	*4.70*
β_{HML}			-0.073	-0.028	0.034	-0.070	-0.020	0.053
t-stat			*-1.41*	*-0.65*	*0.59*	*-1.41*	*-0.45*	*0.86*
β_{MOM}						0.006	0.019	0.028
t-stat						*0.35*	*1.20*	*1.57*
β_{RMW}				-0.212	-0.224		-0.217	-0.232
t-stat				*-5.52*	*-6.15*		*-5.63*	*-6.31*
β_{CMA}					-0.142			-0.156
t-stat					*-2.31*			*-2.50*

Table 13A. Aggregate Volatility Risk Factors in Three- and Five-Factor Fama-French Model

The table presents the alphas and aggregate volatility risk betas from the three-factor and five-factor Fama-French models augmented with additional factors as indicated in the top row of the table. The volatility risk factors are FVIX (the factor-mimicking portfolio tracking the changes in VIX), FIVol (the factor-mimicking portfolio tracking innovations to average idiosyncratic volatility). The test assets on the left-hand side are the nine arbitrage portfolios described in the heading of Table 6A. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

	FF3	**FF3+FVIX+FIVol**			**FF3+CMA**	**FF3+CMA+FVIX+FIVol**			**FF3+RMW**	**FF3+RMW+FVIX+FIVol**			**FF5**	**FF5+FVIX+FIVol**		
	α	α	β_{FVIX}	β_{FIVol}	α	α	β_{FVIX}	β_{FIVol}	α	α	β_{FVIX}	β_{FIVol}	α	α	β_{FVIX}	β_{FIVol}
IVol	0.660	0.333	-1.147	0.105	0.591	0.261	-1.092	0.109	0.435	0.243	-0.737	0.134	0.294	0.127	-0.609	0.144
t-stat	*4.88*	*1.98*	*-5.45*	*2.18*	*4.54*	*1.65*	*-5.14*	*2.29*	*3.52*	*1.48*	*-4.22*	*2.84*	*2.46*	*0.88*	*-3.47*	*3.04*
IVolh	0.801	0.246	-1.183	0.053	0.739	0.151	-1.111	0.059	0.502	0.144	-0.716	0.086	0.356	-0.004	-0.554	0.099
t-stat	*4.16*	*1.05*	*-5.10*	*1.28*	*3.87*	*0.70*	*-4.92*	*1.44*	*2.52*	*0.56*	*-4.08*	*2.41*	*1.87*	*-0.02*	*-3.30*	*2.61*
HMLh	0.369	-0.105	-0.658	-0.216	0.316	-0.170	-0.608	-0.211	0.341	-0.071	-0.814	-0.227	0.265	-0.132	-0.747	-0.221
t-stat	*1.57*	*-0.36*	*-1.76*	*-2.03*	*1.30*	*-0.60*	*-1.68*	*-1.88*	*1.38*	*-0.24*	*-2.08*	*-2.08*	*1.00*	*-0.45*	*-1.87*	*-1.90*
IVol55	-0.532	-0.069	0.803	-0.033	-0.484	-0.031	0.773	-0.035	-0.370	-0.011	0.539	-0.052	-0.271	0.055	0.466	-0.058
t-stat	*-3.84*	*-0.44*	*5.45*	*-1.05*	*-3.54*	*-0.21*	*5.64*	*-1.11*	*-2.71*	*-0.07*	*3.99*	*-1.67*	*-2.04*	*0.37*	*3.85*	*-1.70*
IVol IO	0.993	0.403	-1.441	0.057	0.907	0.359	-1.407	0.060	0.599	0.305	-0.996	0.089	0.455	0.218	-0.900	0.097
t-stat	*3.46*	*1.42*	*-5.32*	*1.01*	*3.19*	*1.28*	*-5.14*	*1.04*	*2.51*	*1.20*	*-4.38*	*1.52*	*1.76*	*0.84*	*-4.01*	*1.60*
IVol Sh	0.880	0.166	-1.370	-0.116	0.805	0.140	-1.350	-0.115	0.274	0.000	-0.613	-0.063	0.120	-0.095	-0.508	-0.054
t-stat	*2.96*	*0.65*	*-5.26*	*-1.68*	*2.87*	*0.56*	*-5.20*	*-1.65*	*1.40*	*0.00*	*-3.36*	*-0.96*	*0.60*	*-0.48*	*-2.71*	*-0.79*
HML IO	1.008	0.423	-1.369	0.029	0.903	0.365	-1.325	0.033	0.720	0.363	-1.094	0.048	0.567	0.273	-0.996	0.057
t-stat	*3.60*	*1.55*	*-7.14*	*0.50*	*3.23*	*1.34*	*-6.84*	*0.55*	*2.99*	*1.43*	*-5.95*	*0.80*	*2.24*	*1.07*	*-5.73*	*0.90*
HML Sh	0.513	-0.086	-0.601	-0.352	0.466	-0.095	-0.594	-0.352	0.247	-0.144	-0.335	-0.333	0.164	-0.177	-0.298	-0.330
t-stat	*2.07*	*-0.38*	*-2.57*	*-3.58*	*1.62*	*-0.46*	*-2.25*	*-3.44*	*0.97*	*-0.68*	*-1.14*	*-3.19*	*0.51*	*-0.90*	*-0.82*	*-2.93*

Table 14A. Aggregate Volatility Risk Factors and the Lottery Factor (FMAX)

Panel A presents alpha and betas of FMAX factor from Bali et al. (2017). The alphas and betas are from the CAPM, Fama and French (1993) three-factor model, and Carhart (1997) model, as well as from those models augmented with FVIX and FIVol (in the columns marked as +VolF). FMAX buys/shorts firms in the top/bottom 30% in terms of maximum returns in the past month. The returns to the long-short strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large (above median) firms, and then averaged. The sorts on maximum/expected skewness are independent of size and use NYSE breakpoints. The maximum return used to form FMAX is the average of the five largest (most positive) daily returns within a month. Panels B and C present alphas and betas of FVIX and FIVol. The alphas and betas are from the CAPM, Fama and French (1993) three-factor model, and Carhart (1997) model, as well as from those models augmented with FVIX and FIVol (in the columns marked as +FMAX). Panels D and E fit the CAPM, the volatility factor model (VolF) and their versions augmented with FMAX (CAPM+FMAX and VolF+FMAX) to the arbitrage portfolios from Table 5A (HML, IVol, IVolh, HMLh, and IVol55). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. FMAX on FVIX and FIVol

	Raw	**CAPM**	**VolF**	**FF3**	**+VolF**	**Carhart**	**+VolF**
$\boldsymbol{\alpha}$	0.326	0.751	0.065	0.609	0.171	0.533	0.046
t-stat	*1.46*	*4.37*	*0.32*	*4.08*	*1.27*	*3.55*	*0.35*
$\boldsymbol{\beta}_{MKT}$		-0.622	-2.488	-0.495	-1.814	-0.470	-1.830
t-stat		*-8.79*	*-5.18*	*-7.23*	*-6.40*	*-7.91*	*-6.68*
$\boldsymbol{\beta}_{SMB}$				-0.484	-0.331	-0.489	-0.350
t-stat				*-5.76*	*-4.79*	*-5.33*	*-4.77*
$\boldsymbol{\beta}_{HML}$				0.451	0.368	0.490	0.394
t-stat				*3.48*	*3.62*	*4.21*	*4.18*
$\boldsymbol{\beta}_{MOM}$						0.099	0.121
t-stat						*1.46*	*1.95*
$\boldsymbol{\beta}_{FVIX}$			-1.376		-0.958		-0.971
t-stat			*-4.05*		*-4.73*		*-5.02*
$\boldsymbol{\beta}_{FIVol}$			-0.040		-0.016		-0.043
t-stat			*-0.90*		*-0.48*		*-1.21*

Panel B. FVIX on FMAX

	Raw	CAPM	+FMax	FF3	+FMax	Carhart	+FMAX
$\boldsymbol{\alpha}$	-1.366	-0.463	-0.286	-0.439	-0.307	-0.444	-0.324
t-stat	*-4.77*	*-4.73*	*-3.06*	*-4.00*	*-3.19*	*-3.92*	*-3.35*
$\boldsymbol{\beta}_{MKT}$		-1.325	-1.471	-1.358	-1.465	-1.357	-1.462
t-stat		*-37.0*	*-36.9*	*-35.2*	*-40.3*	*-34.0*	*-39.8*
$\boldsymbol{\beta}_{SMB}$				0.170	0.065	0.170	0.060
t-stat				*4.94*	*2.68*	*5.08*	*2.68*
$\boldsymbol{\beta}_{HML}$				-0.073	0.025	-0.070	0.040
t-stat				*-1.41*	*0.65*	*-1.41*	*1.09*
$\boldsymbol{\beta}_{MOM}$						0.006	0.028
t-stat						*0.34*	*2.08*
$\boldsymbol{\beta}_{FMAX}$			-0.235		-0.217		-0.225
t-stat			*-7.97*		*-7.72*		*-8.83*

Panel C. FIVol on FMAX

	Raw	CAPM	+FMax	FF3	+FMax	Carhart	+FMAX
$\boldsymbol{\alpha}$	-1.717	-1.193	-1.140	-0.789	-0.923	-1.064	-1.173
t-stat	*-4.66*	*-3.86*	*-2.46*	*-3.19*	*-2.46*	*-3.87*	*-3.23*
$\boldsymbol{\beta}_{MKT}$		-0.999	-1.110	-1.047	-1.117	-0.985	-1.069
t-stat		*-9.21*	*-8.22*	*-13.4*	*-9.99*	*-12.7*	*-10.2*
$\boldsymbol{\beta}_{SMB}$				-0.519	-0.615	-0.512	-0.687
t-stat				*-4.35*	*-3.66*	*-4.80*	*-3.95*
$\boldsymbol{\beta}_{HML}$				-0.819	-0.778	-0.707	-0.566
t-stat				*-6.47*	*-5.04*	*-6.13*	*-4.40*
$\boldsymbol{\beta}_{MOM}$						0.317	0.410
t-stat						*2.89*	*3.01*
$\boldsymbol{\beta}_{FMAX}$			-0.079		-0.047		-0.159
t-stat			*-0.36*		*-0.23*		*-0.81*

Panel D. Value-Weighted Returns

	CAPM	VolF			CAPM+FMAX		VolF+FMAX			
	α	α	β_{FVIX}	β_{FIVol}	α	β_{FMAX}	α	β_{FMAX}	β_{FVIX}	β_{FIVol}
HML	0.310	-0.074	-0.429	-0.152	0.033	0.370	-0.099	0.381	0.096	-0.137
t-stat	*1.56*	*-0.40*	*-1.85*	*-5.05*	*0.20*	*4.16*	*-0.66*	*4.87*	*0.78*	*-4.83*
IVol	0.896	0.128	-1.915	0.097	-0.006	1.202	0.055	1.128	-0.363	0.142
t-stat	*3.51*	*0.51*	*-4.40*	*1.62*	*-0.03*	*24.2*	*0.35*	*18.6*	*-2.85*	*5.25*
IVolh	0.965	0.009	-2.103	0.014	-0.005	1.292	-0.068	1.186	-0.471	0.061
t-stat	*3.28*	*0.03*	*-4.52*	*0.23*	*-0.02*	*13.0*	*-0.28*	*10.6*	*-2.85*	*1.56*
HMLh	0.767	-0.104	-0.837	-0.397	0.576	0.255	-0.107	0.040	-0.782	-0.395
t-stat	*2.14*	*-0.30*	*-2.94*	*-3.82*	*1.39*	*1.40*	*-0.31*	*0.22*	*-2.22*	*-3.60*
IVol55	-0.665	0.121	1.586	0.042	0.062	-0.968	0.178	-0.879	0.376	0.007
t-stat	*-2.89*	*0.47*	*4.61*	*0.99*	*0.36*	*-13.3*	*0.98*	*-11.1*	*2.36*	*0.21*

Panel E. Equal-Weighted Returns

	CAPM	VolF			CAPM+FMAX		VolF+FMAX			
	α	α	β_{FVIX}	β_{FIVol}	α	β_{FMAX}	α	β_{FMAX}	β_{FVIX}	β_{FIVol}
IVol	0.789	0.126	-1.409	-0.009	-0.215	0.938	0.048	0.981	-0.193	0.197
t-stat	*4.13*	*0.51*	*-4.05*	*-0.19*	*-1.08*	*8.98*	*0.29*	*8.16*	*-1.28*	*3.88*
IVolh	1.151	0.090	-2.082	-0.080	-0.254	1.234	-0.141	1.253	-0.373	0.085
t-stat	*4.08*	*0.27*	*-3.70*	*-1.19*	*-1.11*	*9.01*	*-0.65*	*8.26*	*-1.74*	*1.68*
HMLh	1.092	0.303	-0.812	-0.339	1.339	0.350	0.872	0.273	-0.257	-0.350
t-stat	*3.64*	*1.09*	*-2.81*	*-6.82*	*4.73*	*2.22*	*3.51*	*2.26*	*-1.17*	*-6.50*
IVol55	-0.888	-0.107	1.632	0.021	0.099	-0.938	-0.088	-0.969	0.389	-0.140
t-stat	*-3.87*	*-0.35*	*3.72*	*0.39*	*0.37*	*-7.56*	*-0.35*	*-6.80*	*2.00*	*-2.79*

Table 15A. Aggregate Volatility, Liquidity Risk, and Funding Liquidity

Panel A presents partial correlations, conditional on the market return, of FIVOL and FVIX with non-tradable and tradable ($\Delta\gamma_{PS}$ and VW_{PS}) liquidity risk factors from Pastor and Stambaugh (2003), with two liquidity risk factors from Sadka (2006), with the TED spread and TERM spread, as well as with the two versions (LEVnew and LEVold) of the broker-dealer leverage factor from Adrian et al. (2014) and with the non-tradable and tradable versions of the factor based on equity capital ratio of primary dealers from He et al. (2017). Correlations above the diagonal use the full sample (January 1986 to December 2017), while correlations below the diagonal require the data on the two Sadka factors to be available (WRDS coverage of the Sadka factors ends in 2008). Panels B and C report the intercept/alpha and the loading on one of the liquidity risk/funding liquidity factor (as indicated in the name of the column) from the two-factor model with the market factor and the said liquidity risk/funding liquidity factor (CAPM+LiqF), from the three-factor Fama and French (1993) model augmented with the said factor (FF3+LiqF) and the Carhart model augmented with the said factor (Carh+LiqF). Detailed definitions of all variables are in Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Partial Correlations of FVIX and FIVol with Liquidity Risk and Funding Liquidity Factors

	FVIX	FIVOL	$\Delta\gamma_{PS}$	VW_{PS}	PV_{Sadka}	TF_{Sadka}	TED	TERM	CAPF	INT_{VW}	LEVnew	LEVold
FVIX		-0.065	0.054	0.039			-0.161	0.041	-0.074	-0.095	-0.082	0.021
t-stat		*-1.27*	*1.05*	*0.77*			*-3.18*	*0.81*	*-1.45*	*-1.87*	*-0.92*	*0.23*
FIVOL	-0.016		-0.118	-0.320			0.220	-0.087	-0.216	-0.206	0.271	0.167
t-stat	*-0.27*		*-2.31*	*-6.59*			*4.39*	*-1.71*	*-4.31*	*-4.10*	*3.14*	*1.88*
$\Delta\gamma_{PS}$	0.015	-0.172		0.129			-0.209	0.047	0.078	0.083	0.053	0.044
t-stat	*0.25*	*-2.89*		*2.54*			*-4.17*	*0.92*	*1.53*	*1.62*	*0.59*	*0.49*
VW_{PS}	0.039	-0.378	0.180				-0.092	-0.040	-0.001	-0.026	-0.013	0.040
t-stat	*0.65*	*-6.74*	*3.02*				*-1.80*	*-0.78*	*-0.02*	*-0.51*	*-0.15*	*0.45*
PV_{Sadka}	0.098	-0.253	0.198	0.071								
t-stat	*1.62*	*-4.31*	*3.33*	*1.18*								
TF_{Sadka}	0.049	-0.161	0.102	0.039	0.168							
t-stat	*0.81*	*-2.68*	*1.69*	*0.65*	*2.81*							
TED	-0.167	0.322	-0.181	-0.151	-0.289	-0.236		-0.364	-0.023	-0.014	-0.140	-0.078
t-stat	*-2.79*	*5.61*	*-3.04*	*-2.52*	*-4.98*	*-4.01*		*-7.62*	*-0.44*	*-0.27*	*-1.58*	*-0.87*
TERM	0.031	-0.049	0.024	-0.032	-0.015	0.041	-0.264		0.003	-0.051	-0.100	-0.206
t-stat	*0.50*	*-0.82*	*0.39*	*-0.52*	*-0.25*	*0.68*	*-4.51*		*0.05*	*-0.99*	*-1.11*	*-2.34*
CAPF	-0.126	-0.136	0.112	0.009	-0.047	0.093	-0.087	0.021		0.797	-0.001	0.026
t-stat	*-2.10*	*-2.26*	*1.85*	*0.14*	*-0.78*	*1.54*	*-1.45*	*0.35*		*25.73*	*-0.01*	*0.29*
INT_{VW}	-0.206	-0.106	0.131	-0.004	-0.056	0.068	-0.125	-0.003	0.783		0.163	0.116
t-stat	*-3.47*	*-1.75*	*2.18*	*-0.06*	*-0.93*	*1.12*	*-2.09*	*-0.05*	*20.79*		*1.84*	*1.30*
LEVnew	-0.156	0.303	0.043	0.025	0.184	0.354	-0.207	-0.047	0.075	0.266		0.678
t-stat	*-1.49*	*3.00*	*0.40*	*0.24*	*1.76*	*3.57*	*-2.00*	*-0.44*	*0.71*	*2.60*		*10.26*
LEVold	-0.058	0.178	0.040	0.063	-0.029	0.212	-0.132	-0.159	0.123	0.212	0.650	
t-stat	*-0.54*	*1.70*	*0.37*	*0.59*	*-0.28*	*2.04*	*-1.25*	*-1.52*	*1.17*	*2.05*	*8.07*	

Panel B. FVIX on Liquidity Risk and Funding Liquidity Factors

LiqF=	$\Delta\gamma_{PS}$	VW_{PS}	PV_{Sadka}	TF_{Sadka}	TED	TERM	CAPF	INT_{VW}	LEVnew	LEVold
$\alpha_{CAPM+LiqF}$	-0.462	-0.467	-0.486	-0.491	-0.464	-0.464	-0.471	-0.456	-1.454	-1.474
t-stat	*-4.75*	*-4.55*	*-4.32*	*-4.20*	*-4.67*	*-4.78*	*-5.09*	*-4.51*	*-4.20*	*-3.73*
β_{LiqF}	1.294	1.519	26.93	32.14	0.097	0.070	-2.315	-3.451	0.101	0.034
t-stat	*0.73*	*0.51*	*1.62*	*0.74*	*0.21*	*0.13*	*-0.80*	*-0.82*	*1.44*	*0.84*
$\alpha_{FF+LiqF}$	-0.438	-0.444	-0.448	-0.452	-0.440	-0.440	-0.431	-0.439	-1.373	-1.404
t-stat	*-4.00*	*-3.85*	*-3.30*	*-3.24*	*-3.95*	*-4.06*	*-4.15*	*-3.98*	*-3.52*	*-3.18*
β_{LiqF}	1.495	1.535	17.15	24.98	0.115	0.067	1.399	1.861	0.114	0.043
t-stat	*0.95*	*0.52*	*1.00*	*0.64*	*0.25*	*0.14*	*0.72*	*0.63*	*1.69*	*1.20*
$\alpha_{Carh+LiqF}$	-0.442	-0.449	-0.463	-0.469	-0.445	-0.446	-0.437	-0.446	-1.359	-1.368
t-stat	*-3.92*	*-3.78*	*-3.38*	*-3.31*	*-3.84*	*-4.00*	*-4.04*	*-3.85*	*-3.52*	*-3.23*
β_{LiqF}	1.496	1.521	15.42	23.30	0.127	0.109	1.548	2.087	0.115	0.046
t-stat	*0.95*	*0.51*	*0.87*	*0.60*	*0.27*	*0.24*	*0.74*	*0.67*	*1.69*	*1.24*

Panel C. FIVol on Liquidity Risk and Funding Liquidity Factors

LiqF=	$\Delta\gamma_{PS}$	VW_{PS}	PV_{Sadka}	TF_{Sadka}	TED	TERM	CAPF	INT_{VW}	LEVnew	LEVold
$\alpha_{CAPM+LiqF}$	-1.231	-1.041	-1.240	-1.173	-1.257	-1.140	-1.335	-1.148	-2.770	-2.815
t-stat	*-2.62*	*-2.44*	*-2.47*	*-2.16*	*-2.76*	*-2.59*	*-2.85*	*-2.69*	*-1.49*	*-1.50*
β_{LiqF}	-13.27	-58.15	-302.23	-460.02	4.413	-5.227	-31.64	-34.99	-0.145	0.020
t-stat	*-1.72*	*-4.34*	*-2.16*	*-1.91*	*2.33*	*-1.78*	*-2.55*	*-2.01*	*-0.91*	*0.20*
$\alpha_{FF+LiqF}$	-0.987	-0.788	-0.859	-0.805	-1.011	-0.895	-1.077	-0.975	-2.154	-2.198
t-stat	*-2.74*	*-2.42*	*-2.14*	*-1.78*	*-2.93*	*-2.71*	*-2.66*	*-2.70*	*-1.62*	*-1.63*
β_{LiqF}	-11.86	-59.34	-242.04	-230.83	4.821	-5.147	-18.29	-14.02	0.036	0.118
t-stat	*-1.61*	*-4.32*	*-1.47*	*-1.26*	*2.06*	*-1.81*	*-1.34*	*-0.72*	*0.24*	*1.41*
$\alpha_{Carh+LiqF}$	-1.288	-1.093	-1.209	-1.099	-1.336	-1.208	-1.327	-1.271	-2.415	-2.340
t-stat	*-3.32*	*-3.15*	*-2.74*	*-2.22*	*-3.65*	*-3.38*	*-3.22*	*-3.34*	*-1.80*	*-1.72*
β_{LiqF}	-11.81	-60.27	-281.81	-259.70	5.565	-3.024	-11.63	-4.30	0.023	0.107
t-stat	*-1.72*	*-4.31*	*-1.79*	*-1.39*	*2.57*	*-1.40*	*-0.93*	*-0.26*	*0.15*	*1.12*

Table 16A. Aggregate Volatility Risk and Stambaugh and Yuan (2017) Factors

Panels A-C report alphas and betas of three asset-pricing factors from Stambaugh and Yuan (2017): the size factor (SMBSY), the ”performance” factor (PERF), and the ”management” factor (MGMT). The alphas and betas are from the CAPM, Fama and French (1993) three-factor model, and Carhart (1997) model, as well as from those models augmented with FVIX and FIVol (in the columns marked as +VolF). Panels D and E report alphas and betas of FVIX and FIVol, respectively, estimated from the CAPM, the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, the Stambaugh and Yuan (2017) model, and the five-factor Fama and French (2015) model (FF5), as well as from the Stambaugh and Yuan (2017) model augmented with the momentum factor (SY+MOM) and the five-factor Fama and French (2015) model augmented with MGMT and PERF factors from Stambaugh and Yuan (2017). Detailed definitions of Stambaugh and Yuan (2017) factors are in Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. SMBSY on FVIX and FIVol

	Raw	**CAPM**	**+FVIX**	**+FVIX+FIVol**	**FF3**	**+FVIX**	**+FVIX+FIVol**	**Carhart**	**+FVIX**	**+FVIX+FIVol**
α	0.449	0.363	0.541	0.422	0.201	0.204	0.203	0.163	0.178	0.167
t-stat	*3.76*	*3.06*	*3.11*	*2.24*	*5.31*	*3.99*	*3.66*	*4.00*	*3.38*	*2.92*
β_{MKT}		0.169	1.009	0.884	0.007	0.006	0.005	0.015	0.010	0.000
t-stat		*4.92*	*3.38*	*2.44*	*0.54*	*0.07*	*0.05*	*1.22*	*0.12*	*0.00*
β_{SMB}					0.883	0.846	0.845	0.882	0.845	0.840
t-stat					*45.5*	*38.1*	*42.8*	*40.9*	*35.9*	*40.1*
β_{HML}					0.033	0.033	0.032	0.048	0.045	0.039
t-stat					*1.77*	*1.70*	*1.48*	*2.44*	*2.28*	*1.92*
β_{MOM}								0.042	0.032	0.035
t-stat								*3.16*	*2.06*	*2.27*
β_{FVIX}			0.675	0.650		0.000	0.000		-0.002	-0.004
t-stat			*3.08*	*2.55*		*0.00*	*0.00*		*-0.04*	*-0.06*
β_{FIVol}				-0.087			-0.001			-0.009
t-stat				*-2.36*			*-0.08*			*-0.81*

Panel B. PERF on FVIX and FIVol

	Raw	CAPM	+FVIX	+FVIX+FIVol	FF3	+FVIX	+FVIX+FIVol	Carhart	+FVIX	+FVIX+FIVol
$\boldsymbol{\alpha}$	0.678	0.786	0.808	0.989	1.039	0.926	0.977	0.523	0.447	0.330
t-stat	*4.29*	*5.17*	*3.36*	*4.24*	*8.48*	*4.95*	*5.31*	*5.01*	*3.24*	*2.33*
$\boldsymbol{\beta}_{MKT}$		-0.211	-0.744	-0.553	-0.284	-1.030	-0.966	-0.175	-0.947	-1.054
t-stat		*-3.02*	*-2.10*	*-1.57*	*-4.92*	*-3.93*	*-3.41*	*-5.28*	*-4.12*	*-4.94*
$\boldsymbol{\beta}_{SMB}$					-0.075	-0.067	-0.039	-0.082	-0.086	-0.136
t-stat					*-1.32*	*-0.85*	*-0.45*	*-1.42*	*-1.32*	*-2.29*
$\boldsymbol{\beta}_{HML}$					-0.528	-0.564	-0.523	-0.323	-0.333	-0.390
t-stat					*-3.71*	*-2.94*	*-2.57*	*-3.07*	*-2.70*	*-3.66*
$\boldsymbol{\beta}_{MOM}$								0.581	0.587	0.621
t-stat								*12.22*	*10.65*	*10.85*
$\boldsymbol{\beta}_{FVIX}$			-0.294	-0.256		-0.458	-0.451		-0.506	-0.521
t-stat			*-1.25*	*-1.19*		*-2.57*	*-2.41*		*-3.26*	*-3.85*
$\boldsymbol{\beta}_{FIVol}$				0.132			0.050			-0.087
t-stat				*2.02*			*0.78*			*-2.29*

Panel C. MGMT on FVIX and FIVol

	Raw	CAPM	+FVIX	+FVIX+FIVol	FF3	+FVIX	+FVIX+FIVol	Carhart	+FVIX	+FVIX+FIVol
$\boldsymbol{\alpha}$	0.582	0.755	0.477	0.416	0.512	0.439	0.472	0.453	0.369	0.389
t-stat	*4.66*	*6.61*	*3.42*	*3.14*	*7.07*	*3.94*	*4.35*	*6.46*	*3.61*	*3.78*
$\boldsymbol{\beta}_{MKT}$		-0.338	-1.057	-1.121	-0.202	-0.526	-0.484	-0.189	-0.514	-0.495
t-stat		*-8.63*	*-3.87*	*-4.45*	*-8.42*	*-4.60*	*-3.67*	*-9.26*	*-5.02*	*-4.00*
$\boldsymbol{\beta}_{SMB}$					-0.190	-0.137	-0.118	-0.191	-0.139	-0.131
t-stat					*-4.63*	*-2.43*	*-2.07*	*-5.15*	*-2.78*	*-2.59*
$\boldsymbol{\beta}_{HML}$					0.602	0.560	0.587	0.626	0.594	0.604
t-stat					*13.00*	*8.50*	*8.84*	*14.66*	*9.77*	*9.79*
$\boldsymbol{\beta}_{MOM}$								0.067	0.085	0.079
t-stat								*2.37*	*2.35*	*1.87*
$\boldsymbol{\beta}_{FVIX}$			-0.566	-0.578		-0.238	-0.233		-0.245	-0.242
t-stat			*-3.20*	*-3.66*		*-2.89*	*-2.80*		*-3.29*	*-3.15*
$\boldsymbol{\beta}_{FIVol}$				-0.044			0.032			0.015
t-stat				*-1.49*			*1.46*			*0.54*

Panel D. FVIX on Stambaugh and Yuan (2017) Factors

	Raw	**CAPM**	**FF3**	**SY**	**Carhart**	**SY+MOM**	**FF5**	**SY+CMA+RMW**
$\boldsymbol{\alpha}$	-1.366	-0.463	-0.439	-0.354	-0.444	-0.329	-0.305	-0.321
t-stat	*-4.77*	*-4.73*	*-4.00*	*-3.47*	*-3.92*	*-3.58*	*-3.73*	*-3.64*
$\boldsymbol{\beta}_{MKT}$		-1.325	-1.358	-1.402	-1.357	-1.412	-1.407	-1.411
t-stat		*-36.98*	*-35.18*	*-42.85*	*-34.00*	*-44.91*	*-50.70*	*-47.63*
$\boldsymbol{\beta}_{SMB}$			0.170		0.170		0.107	
t-stat			*4.94*		*5.08*		*4.56*	
$\boldsymbol{\beta}_{SMBSY}$				0.153		0.135		0.109
t-stat				*3.49*		*4.05*		*5.09*
$\boldsymbol{\beta}_{HML}$			-0.073		-0.070		0.034	0.075
t-stat			*-1.41*		*-1.41*		*0.59*	*1.01*
$\boldsymbol{\beta}_{MOM}$					0.006	0.087		
t-stat					*0.34*	*3.41*		
$\boldsymbol{\beta}_{CMA}$							-0.142	-0.131
t-stat							*-2.31*	*-1.87*
$\boldsymbol{\beta}_{RMW}$							-0.224	-0.251
t-stat							*-6.15*	*-5.30*
$\boldsymbol{\beta}_{MGMT}$				-0.142		-0.152		-0.052
t-stat				*-4.14*		*-5.18*		*-1.39*
$\boldsymbol{\beta}_{PERF}$				-0.044		-0.117		0.023
t-stat				*-1.89*		*-3.88*		*0.91*

Panel E. FIVol on Stambaugh and Yuan (2017) Factors

	Raw	**CAPM**	**FF3**	**SY**	**Carhart**	**SY+MOM**	**FF5**	**SY+CMA+RMW**
$\boldsymbol{\alpha}$	-1.943	-1.220	-0.974	-1.172	-1.275	-0.997	-0.774	-1.107
t-stat	*-3.73*	*-2.59*	*-2.68*	*-2.84*	*-3.28*	*-2.67*	*-1.95*	*-2.80*
$\boldsymbol{\beta}_{MKT}$		-1.061	-1.093	-0.971	-0.995	-1.046	-1.168	-1.010
t-stat		*-6.59*	*-10.30*	*-9.51*	*-8.68*	*-9.95*	*-9.80*	*-9.30*
$\boldsymbol{\beta}_{SMB}$			-0.594		-0.611		-0.682	-0.598
t-stat			*-3.71*		*-4.54*		*-4.69*	*-3.22*
$\boldsymbol{\beta}_{SMBSY}$				-0.630		-0.754		
t-stat				*-2.84*		*-4.26*		
$\boldsymbol{\beta}_{HML}$			-0.801		-0.646		-0.633	-0.488
t-stat			*-4.37*		*-3.76*		*-3.13*	*-2.60*
$\boldsymbol{\beta}_{MOM}$					0.392	0.620		
t-stat					*3.10*	*3.32*		
$\boldsymbol{\beta}_{CMA}$							-0.240	-0.928
t-stat							*-0.88*	*-2.63*
$\boldsymbol{\beta}_{RMW}$							-0.318	-0.639
t-stat							*-1.80*	*-2.95*
$\boldsymbol{\beta}_{MGMT}$				-0.332		-0.404		0.731
t-stat				*-1.14*		*-1.49*		*1.96*
$\boldsymbol{\beta}_{PERF}$				0.337		-0.184		0.347
t-stat				*2.06*		*-0.92*		*2.11*

Table 17A. Explaining the Value Effect and the Idiosyncratic Volatility Discount with Stambaugh and Yuan (2017) Factors and Aggregate Volatility Risk Factors

The table fits the CAPM, the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, and the volatility factor model (VolF), as well as the Stambaugh and Yuan (2017) model (SY) and its version augmented with FVIX and FIVol (SY+FVIX+FIVol) to the arbitrage portfolios from Table 5A (HML, IVol, IVolh, HMLh, and IVol55). Definitions of Stambaugh and Yuan (2017) factors are in Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Value-Weighted Returns

	CAPM	FF3	Carhart	VolF Model			Stambaugh and Yuan (2017)				Stambaugh and Yuan (2017) + FVIX + FIVol					
	α	α	α	α	β_{FVIX}	β_{FIVol}	α	β_{SMBSY}	β_{MGMT}	β_{PERF}	α	β_{SMBSY}	β_{MGMT}	β_{PERF}	β_{FVIX}	β_{FIVol}
HML	0.310			-0.074	-0.429	-0.152	-0.022	0.086	0.749	-0.221	-0.162	0.045	0.705	-0.195	-0.101	-0.089
t-stat	*1.56*			*-0.40*	*-1.85*	*-5.05*	*-0.17*	*1.03*	*7.99*	*-4.16*	*-1.30*	*0.68*	*7.68*	*-4.11*	*-0.67*	*-4.48*
IVol	0.896	0.660	0.457	0.128	-1.915	0.097	-0.080	-0.738	1.014	0.376	-0.365	-0.566	0.894	0.320	-0.947	0.043
t-stat	*3.51*	*4.88*	*3.25*	*0.51*	*-4.40*	*1.62*	*-0.42*	*-5.79*	*13.4*	*4.77*	*-2.17*	*-5.47*	*10.9*	*4.45*	*-3.72*	*1.21*
IVolh	0.965	0.801	0.603	0.009	-2.103	0.014	-0.184	-0.745	1.309	0.361	-0.559	-0.622	1.163	0.331	-0.947	-0.034
t-stat	*3.28*	*4.16*	*3.17*	*0.03*	*-4.52*	*0.23*	*-0.80*	*-4.99*	*13.3*	*6.19*	*-2.51*	*-5.08*	*10.5*	*5.17*	*-3.93*	*-0.94*
HMLh	0.767	0.369	0.641	-0.104	-0.837	-0.397	0.665	0.420	0.856	-0.579	0.057	0.389	0.648	-0.530	-0.862	-0.258
t-stat	*2.14*	*1.57*	*2.33*	*-0.30*	*-2.94*	*-3.82*	*1.52*	*2.48*	*5.37*	*-4.13*	*0.16*	*2.65*	*4.12*	*-5.15*	*-2.74*	*-3.33*
IVol55	-0.665	-0.532	-0.416	0.121	1.586	0.042	0.094	0.498	-1.069	-0.093	0.416	0.411	-0.946	-0.075	0.758	0.046
t-stat	*-2.89*	*-3.84*	*-2.94*	*0.47*	*4.61*	*0.99*	*0.50*	*3.61*	*-11.8*	*-1.70*	*2.22*	*3.68*	*-10.1*	*-1.49*	*3.97*	*1.57*

Panel B. Equal-Weighted Returns

	CAPM	FF3	Carhart	VolF Model			Stambaugh and Yuan (2017)				Stambaugh and Yuan (2017) + FVIX + FIVol					
	α	α	α	α	β_{FVIX}	β_{FIVol}	α	β_{SMBSY}	β_{MGMT}	β_{PERF}	α	β_{SMBSY}	β_{MGMT}	β_{PERF}	β_{FVIX}	β_{FIVol}
IVol	0.789	0.633	0.529	0.126	-1.409	-0.009	0.146	-0.629	0.760	0.221	-0.137	-0.578	0.655	0.216	-0.593	-0.063
t-stat	*4.13*	*4.74*	*5.56*	*0.51*	*-4.05*	*-0.19*	*1.19*	*-5.10*	*11.7*	*4.27*	*-0.98*	*-6.17*	*14.5*	*5.03*	*-3.81*	*-2.30*
IVolh	1.151	0.865	0.672	0.090	-2.082	-0.080	0.173	-0.884	1.200	0.305	-0.308	-0.852	1.029	0.319	-0.847	-0.155
t-stat	*4.08*	*4.94*	*4.07*	*0.27*	*-3.70*	*-1.19*	*0.76*	*-4.28*	*11.0*	*3.96*	*-1.45*	*-5.66*	*11.5*	*5.15*	*-3.35*	*-3.86*
HMLh	1.092	0.703	0.723	0.303	-0.812	-0.339	0.628	0.001	1.001	-0.256	0.197	-0.141	0.868	-0.170	-0.263	-0.289
t-stat	*3.64*	*4.35*	*5.41*	*1.09*	*-2.81*	*-6.82*	*2.54*	*0.00*	*7.93*	*-2.66*	*0.87*	*-1.36*	*10.2*	*-2.86*	*-1.75*	*-8.03*
IVol55	-0.888	-0.644	-0.534	-0.107	1.632	0.021	-0.247	0.991	-0.975	-0.155	0.014	0.982	-0.883	-0.167	0.434	0.092
t-stat	*-3.87*	*-5.75*	*-4.76*	*-0.35*	*3.72*	*0.39*	*-1.55*	*7.74*	*-14.7*	*-2.83*	*0.09*	*9.68*	*-14.9*	*-3.89*	*3.44*	*3.51*

Table 18A. FVIX/FIVol Factor Returns and the Business Cycle

Panel A (B) presents the slopes from the regressions of the business cycle variables on the FVIX (FIVol) factor returns. The business cycle variables are the NBER recession dummy, the log of the VIX index, the log market volatility forecast from TARCH(1,1) model, and the log realized market volatility. The regression with the NBER dummy is the probit regression. The numbers in the first row are the number of months by which we lag the FVIX (FIVol) factor returns in each column. The slopes (with the exception of the probit regression) indicate the change in the business cycles variables (in percentage points) in response to 1% return to the FVIX (FIVol) factor. For the probit regression, the table reports the slope (in the "NBER" row) and the marginal effect evaluated at the mean value of FVIX (in the "Marginal" row).

Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). Average IVol is the simple average of the idiosyncratic volatilities of all firms traded during the given month. The NBER recession dummy is one for the months between NBER-announced peak and trough and zero otherwise. VIX index is from CBOE and measures the implied volatility of the one-month options on S&P 100. The TARCH(1,1) model is fitted to monthly returns to the CRSP value-weighted index. The realized market volatility is the square root of the average squared daily return to the market portfolio (CRSP value-weighted index) within each given month. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Business Cycle Variables Predicted by FVIX Factor Returns

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
NBER	3.957	3.898	6.719	6.291	3.505	0.986	0.635	1.538	0.798
Marginal	0.623	0.658	1.151	1.081	0.623	0.178	0.115	0.278	0.144
t-stat	*1.82*	*1.88*	*3.35*	*3.24*	*1.85*	*0.51*	*0.32*	*0.80*	*0.41*
VIX	0.015	0.316	0.529	0.786	1.851	-0.211	-0.061	0.055	-0.021
t-stat	*0.05*	*1.04*	*1.76*	*2.35*	*5.21*	*-0.66*	*-0.18*	*0.18*	*-0.09*
TARCH	0.345	0.459	0.715	1.053	1.215	-0.149	-0.084	0.078	0.046
t-stat	*1.43*	*1.68*	*2.81*	*3.66*	*3.69*	*-0.52*	*-0.31*	*0.30*	*0.20*
Realized	0.270	0.509	0.682	0.818	2.263	0.024	-0.110	0.017	0.030
t-stat	*0.76*	*1.15*	*1.79*	*1.70*	*4.25*	*0.05*	*-0.23*	*0.04*	*0.09*
$\overline{IVOL}$	0.160	0.325	0.493	0.608	0.531	0.173	0.069	0.170	0.093
t-stat	*0.69*	*1.33*	*2.17*	*2.58*	*1.83*	*0.71*	*0.27*	*0.62*	*0.38*

Panel B. Business Cycle Variables Predicted by FIVol Factor Returns

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
NBER	1.654	2.171	3.102	2.869	1.053	0.136	-0.418	-0.738	-2.272
Marginal	0.370	0.482	0.677	0.626	0.234	0.030	-0.093	-0.164	-0.499
t-stat	*1.88*	*2.56*	*3.65*	*3.44*	*1.41*	*0.18*	*-0.55*	*-0.95*	*-2.63*
VIX	-0.108	0.000	0.177	0.457	0.878	-0.804	-0.836	-0.477	-0.499
t-stat	*-0.38*	*0.00*	*0.48*	*1.06*	*1.86*	*-2.28*	*-1.97*	*-1.43*	*-1.95*
TARCH	0.094	0.206	0.364	0.409	0.357	-0.504	-0.609	-0.350	-0.373
t-stat	*0.57*	*1.01*	*1.39*	*1.32*	*1.15*	*-2.05*	*-2.55*	*-2.04*	*-2.49*
Realized	-0.199	0.031	0.488	0.450	1.119	-0.780	-0.957	-0.562	-0.708
t-stat	*-0.66*	*0.10*	*1.27*	*0.93*	*1.95*	*-2.06*	*-1.95*	*-1.51*	*-2.20*
$\overline{IVOL}$	0.038	0.160	0.355	0.318	0.113	-0.291	-0.477	-0.308	-0.396
t-stat	*0.22*	*0.97*	*1.88*	*1.41*	*0.42*	*-1.53*	*-2.14*	*-1.66*	*-2.33*

Table 19A. Alternative Value-Minus-Growth Strategies

The table reports alphas and FVIX and FIVol betas of value-minus-growth strategies based on variables indicated in the column names. Composite sorts firms on the sum of ranks on E/P, CF/P, D/P, and M/B. HMLdev is the value-minus-growth strategy from Asness and Franzini (2013), which is based on market-to-book, but updates firm's market cap monthly. HMLall is the cheap-minus-expensive strategy from Ilmanen et al. (2019) that includes not only the usual value-minus-growth strategy from the equity market, but also its analogues from the fixed income, currency, and commodities markets. The alphas are from the CAPM, the Carhart (1997) model, the five-factor Fama and French (2015) model, and the volatility factor model with the market factor, FVIX, and FIVol. The latter model also supplies the FVIX and FIVol betas in the bottom two rows. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

	E/P	**CF/P**	**D/P**	**Compos**	**HMLdev**	**HMLall**
$\boldsymbol{\alpha}_{CAPM}$	0.381	0.385	0.169	0.524	0.160	0.232
t-stat	*3.05*	*3.28*	*1.66*	*3.01*	*0.76*	*3.23*
$\boldsymbol{\alpha}_{Carhart}$	0.205	0.250	0.117	0.322	0.213	0.264
t-stat	*2.87*	*3.16*	*1.27*	*2.57*	*2.88*	*4.55*
$\boldsymbol{\alpha}_{FF5}$	0.154	0.191	0.117	0.325	-0.044	0.175
t-stat	*2.39*	*2.44*	*1.31*	*2.92*	*-0.27*	*2.37*
$\boldsymbol{\alpha}_{VolF}$	0.151	0.168	0.163	0.357	-0.362	0.115
t-stat	*1.27*	*1.65*	*1.52*	*2.69*	*-1.56*	*1.42*
$\boldsymbol{\beta}_{FVIX}$	-0.269	-0.126	-0.042	0.111	-0.429	-0.143
t-stat	*-2.84*	*-1.56*	*-0.37*	*0.96*	*-1.80*	*-2.16*
$\boldsymbol{\beta}_{FIVol}$	-0.086	-0.130	0.011	-0.179	-0.265	-0.042
t-stat	*-4.98*	*-7.13*	*0.42*	*-6.37*	*-4.44*	*-2.37*

Table 20A. Alternative Growth Options Sorts

The table presents, across quintiles from sorts on alternative growth options measures, average market-to-book values and FVIX and FIVol betas of each quintile portfolio, as well as the difference in market-to-book and the betas between the extreme quintiles. The alternative growth options measures are AG, one-year asset growth rate (Panel A), PVGO, the fraction of the firm value that comes from future growth, calculated as in Bali et al. (2020) (Panel B), PVGO Predicted, the expected value of PVGO from the panel regression of PVGO on its drivers from Trigeorgis and Lambertides (2014) (Panel C), and TVolSens, firm value sensitivity to changes in total volatility of the firm (Panel D). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017 for FVIX and FIVol betas, January 1964 to December 2017 for market-to-book averages in Panel A and Panel D, and April 1978 to December 2017 for market-to-book averages in Panel B and Panel C.

Panel A. Asset Growth Sorts

	Value	GO2	GO3	GO4	Growth	V-G
MB	3.148	2.082	2.100	2.438	3.875	-0.749
t-stat	*10.1*	*18.9*	*30.8*	*31.8*	*24.0*	*-2.89*
β_{FVIX}	-0.098	-0.243	-0.409	-0.144	0.283	-0.382
t-stat	*-1.27*	*-2.31*	*-6.24*	*-1.43*	*2.98*	*-2.94*
β_{FIVol}	-0.062	-0.041	-0.029	-0.028	0.046	-0.108
t-stat	*-3.03*	*-2.62*	*-2.28*	*-1.70*	*2.92*	*-3.35*

Panel B. PVGO Sorts

	Value	GO2	GO3	GO4	Growth	V-G
MB	1.763	2.127	2.623	3.046	3.416	-1.655
t-stat	*23.1*	*23.2*	*22.9*	*25.5*	*21.4*	*-13.5*
β_{FVIX}	-0.345	-0.754	-0.481	-0.129	0.270	-0.614
t-stat	*-1.68*	*-3.98*	*-2.68*	*-1.33*	*3.55*	*-3.23*
β_{FIVol}	-0.168	-0.083	-0.056	-0.004	0.000	-0.168
t-stat	*-6.35*	*-3.17*	*-2.30*	*-0.17*	*-0.02*	*-4.72*

Panel C. Predicted PVGO Sorts

	Value	GO2	GO3	GO4	Growth	V-G
MB	2.139	2.396	2.610	3.437	4.634	-2.483
t-stat	*17.0*	*17.8*	*25.1*	*11.8*	*17.8*	*-9.55*
β_{FVIX}	-0.527	-0.462	-0.441	-0.301	0.231	-0.758
t-stat	*-2.66*	*-2.20*	*-4.10*	*-3.88*	*2.56*	*-3.60*
β_{FIVol}	-0.128	-0.091	-0.075	-0.015	0.065	-0.193
t-stat	*-4.63*	*-3.11*	*-3.44*	*-0.82*	*3.02*	*-4.82*

Panel D. TVolSens Sorts

	Value	**GO2**	**GO3**	**GO4**	**Growth**	**V-G**
MB	2.759	2.617	2.485	2.709	3.237	-0.464
t-stat	*26.1*	*29.6*	*29.6*	*18.6*	*15.5*	*-2.62*
$\boldsymbol{\beta}_{FVIX}$	0.242	0.266	0.229	0.354	0.583	-0.341
t-stat	*3.33*	*3.89*	*3.27*	*3.80*	*3.71*	*-2.70*
$\boldsymbol{\beta}_{FIVol}$	-0.193	-0.180	-0.155	-0.125	-0.088	-0.105
t-stat	*-8.89*	*-8.53*	*-6.87*	*-4.85*	*-2.72*	*-5.32*

Table 21A. Value Effect, Idiosyncratic Volatility Discount, and Exposure to Aggregate Volatility Changes

Panel A reports the sensitivity to aggregate volatility changes of the nine arbitrage portfolios described in the heading of Table 6A. The sensitivity is measured by estimating the following regressions:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta_{\Delta VIX}} \cdot \Delta VIX \tag{A34}$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta_{FVIX}} \cdot FVIX \tag{A35}$$

$\boldsymbol{\beta}_{MKT}$ is from the CAPM fitted to the daily data.

Panels B and C present slopes from the four regressions below (market betas in Models 1-3 are not reported for brevity) fitted to different arbitrage portfolios, the ones from Table 4 in the paper:

$$Model\ 1 \ : \ Ret_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{\Delta VIX} \cdot \Delta VIX_t \tag{A36}$$

$$Model\ 2 \ : \ Ret_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{\Delta VIX} \cdot \Delta VIX_t + \beta_{\Delta IVol} \cdot \Delta IVol_t \tag{A37}$$

$$Model\ 3 \ : \ Ret_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{\Delta VIX} \cdot \Delta VIX_t + \beta_{IVol^U} \cdot \Delta IVol_t^U \tag{A38}$$

$$Model\ 4 \ : \ Ret_t = \alpha + \beta \cdot (MKT_t - RF_t) \tag{A39}$$

The test assets on the left-hand side of the equations above are reported in the leftmost column of each panel and defined in the heading of Table 4R. The regressions are run at daily frequency; $IVOL^U$ is the residual from ARMA(1,1) model fitted to average IVol. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

	Value-Weighted				Equal-Weighted		
	$\beta_{\Delta VIX}$	β_{FVIX}	β_{MKT}		$\beta_{\Delta VIX}$	β_{FVIX}	β_{MKT}
HML	-0.020	-0.280	-0.192				
t-stat	*-2.79*	*-4.09*	*-5.89*				
IVol	-0.090	-2.184	-0.549	**IVol**	-0.031	-1.083	-0.349
t-stat	*-7.02*	*-35.7*	*-12.0*	**t-stat**	*-3.45*	*-25.09*	*-14.9*
IVolh	-0.107	-2.567	-0.607	**IVolh**	-0.039	-1.679	-0.410
t-stat	*-6.20*	*-27.2*	*-11.6*	**t-stat**	*-2.28*	*-20.1*	*-11.2*
HMLh	-0.059	-0.775	-0.377	**HMLh**	-0.032	-0.874	-0.426
t-stat	*-3.65*	*-6.62*	*-7.89*	**t-stat**	*-3.72*	*-13.5*	*-15.1*
IVol55	0.070	1.698	1.466	**IVol55**	0.046	1.677	0.981
t-stat	*4.22*	*20.2*	*40.1*	**t-stat**	*4.47*	*31.7*	*36.5*
IVol IO	-0.069	-2.223	-0.744	**IVol IO**	-0.044	-1.658	-0.659
t-stat	*-3.31*	*-22.0*	*-17.4*	**t-stat**	*-3.24*	*-26.4*	*-21.6*
IVol Sh	-0.082	-1.971	-0.847	**IVol Sh**	-0.031	-1.224	-0.649
t-stat	*-4.11*	*-17.8*	*-15.6*	**t-stat**	*-2.40*	*-17.1*	*-22.9*
HML IO	0.013	-0.258	-1.188	**HML IO**	-0.015	-1.076	-1.186
t-stat	*0.48*	*-1.06*	*-35.4*	**t-stat**	*-0.39*	*-6.18*	*-27.6*
HML Sh	-0.051	-1.023	-0.490	**HML Sh**	-0.019	-0.675	-0.342
t-stat	*-2.91*	*-6.85*	*-9.80*	**t-stat**	*-2.32*	*-7.33*	*-13.0*

Panel B. Value-Weighted Returns

	1	2		3		4
	DVIX	**DVIX joint**	**DIVol**	**DVIX joint**	**UIVol**	**Bmkt**
VMG	-0.034	-0.035	-0.091	-0.035	-0.112	-0.074
t-stat	*-6.16*	*-6.33*	*-2.22*	*-6.32*	*-2.31*	*-9.23*
IVol	-0.084	-0.085	-0.123	-0.086	-0.252	-0.576
t-stat	*-12.6*	*-12.7*	*-2.49*	*-12.9*	*-4.30*	*-59.1*
IVolG	-0.026	-0.027	-0.114	-0.028	-0.251	-0.532
t-stat	*-3.07*	*-3.21*	*-1.81*	*-3.31*	*-3.37*	*-43.2*
VMGh	-0.016	-0.017	-0.066	-0.018	-0.119	-0.141
t-stat	*-1.93*	*-2.02*	*-1.04*	*-2.05*	*-1.60*	*-11.4*
HiVolG	0.037	0.038	0.105	0.039	0.214	1.378
t-stat	*5.75*	*5.92*	*2.21*	*6.02*	*3.81*	*148.4*

Panel C. Equal-Weighted Returns

	1	2		3		4
	DVIX	**DVIX joint**	**DIVol**	**DVIX joint**	**UIVol**	**Bmkt**
VMG	-0.022	-0.023	-0.116	-0.023	-0.175	-0.129
t-stat	*-5.56*	*-5.88*	*-4.06*	*-5.93*	*-5.18*	*-23.1*
IVol	-0.042	-0.043	-0.085	-0.044	-0.235	-0.436
t-stat	*-10.3*	*-10.5*	*-2.79*	*-10.8*	*-6.52*	*-72.6*
IVolG	-0.054	-0.055	-0.092	-0.056	-0.224	-0.484
t-stat	*-10.35*	*-10.52*	*-2.37*	*-10.7*	*-4.86*	*-63.3*
VMGh	-0.026	-0.028	-0.127	-0.028	-0.201	-0.167
t-stat	*-4.80*	*-5.05*	*-3.13*	*-5.10*	*-4.21*	*-21.1*
HiVolG	0.059	0.060	0.047	0.061	0.151	1.105
t-stat	*11.8*	*11.9*	*1.26*	*12.0*	*3.43*	*150.9*

Table 22A. Double Sorts on Idiosyncratic Volatility and Market-to-Book: Table 3 from the Paper Re-Done with Equal-Weighted Returns

The table presents equal-weighted CAPM alphas (Panel A), equal-weightedalphas from the volatility factor model with the market factor, FVIX and FIVol (Panel B), as well as FVIX and FIVol betas from the volatility factor model (Panels C and D, respectively) for the 25 IVol - market-to-book portfolios. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The portfolios are sorted using NYSE (`exchcd`=1) breakpoints. The IVol (market-to-book) portfolios are rebalanced monthly (annually). The FVIX and FIVol betas estimates are from the volatility factor model with the market factor, FVIX and FIVol. FVIX (FIVol) is the aggregate (idiosyncratic) volatility risk factor that tracks innovations to VIX ($\overline{IVOL}$). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. CAPM Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	0.392	0.473	0.657	0.317	0.204	0.188
t-stat	*2.30*	*2.12*	*2.90*	*1.50*	*0.88*	*1.20*
MB2	0.323	0.338	0.303	0.305	-0.124	0.448
t-stat	*2.18*	*2.04*	*1.66*	*1.39*	*-0.65*	*2.90*
MB3	0.255	0.341	0.272	0.261	-0.144	0.399
t-stat	*1.67*	*2.18*	*1.72*	*1.49*	*-0.80*	*2.19*
MB4	0.326	0.376	0.102	0.097	-0.449	0.775
t-stat	*2.24*	*2.53*	*0.67*	*0.60*	*-2.50*	*3.61*
Growth	0.263	0.183	-0.016	-0.071	-0.888	1.151
t-stat	*2.26*	*1.48*	*-0.13*	*-0.46*	*-3.87*	*4.08*
V-G	0.129	0.290	0.672	0.389	1.092	0.963
t(V-G)	*0.84*	*1.41*	*2.74*	*1.61*	*3.64*	*3.62*

Panel B. Three-Factor Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	0.140	0.155	0.395	0.090	0.196	-0.056
t-stat	*1.03*	*0.92*	*2.12*	*0.56*	*0.87*	*-0.29*
MB2	0.046	0.194	0.111	0.046	-0.025	0.071
t-stat	*0.39*	*1.42*	*0.77*	*0.30*	*-0.12*	*0.35*
MB3	-0.023	0.031	0.063	0.093	0.087	-0.110
t-stat	*-0.17*	*0.21*	*0.48*	*0.63*	*0.39*	*-0.43*
MB4	0.063	0.104	-0.037	0.051	-0.046	0.109
t-stat	*0.59*	*0.86*	*-0.31*	*0.32*	*-0.18*	*0.41*
Growth	-0.017	0.031	0.080	0.241	-0.107	0.090
t-stat	*-0.18*	*0.26*	*0.60*	*1.30*	*-0.35*	*0.27*
V-G	0.157	0.124	0.315	-0.151	0.303	0.146
t(V-G)	*1.04*	*0.74*	*1.38*	*-0.70*	*1.09*	*0.56*

Panel C. FVIX Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Value	0.019	0.103	0.219	0.264	0.821	-0.802
t-stat	*0.22*	*0.90*	*1.75*	*2.08*	*4.08*	*-4.10*
MB2	-0.116	0.112	0.184	0.115	0.793	-0.909
t-stat	*-1.74*	*1.05*	*1.94*	*1.21*	*4.53*	*-5.10*
MB3	-0.239	-0.258	-0.039	0.160	0.918	-1.157
t-stat	*-2.28*	*-1.60*	*-0.43*	*1.11*	*3.92*	*-3.83*
MB4	-0.295	-0.251	0.107	0.292	1.075	-1.369
t-stat	*-3.26*	*-2.65*	*1.05*	*2.69*	*3.42*	*-3.95*
Growth	-0.450	-0.179	0.338	0.722	1.632	-2.082
t-stat	*-2.98*	*-2.02*	*4.25*	*3.32*	*3.72*	*-3.70*
V-G	0.469	0.283	-0.120	-0.458	-0.812	-1.280
t(V-G)	*2.89*	*2.50*	*-0.83*	*-2.58*	*-2.81*	*-3.27*

Panel D. FIVol Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Value	-0.213	-0.299	-0.297	-0.287	-0.318	0.104
t-stat	*-8.78*	*-8.25*	*-7.95*	*-8.14*	*-5.89*	*2.21*
MB2	-0.184	-0.161	-0.227	-0.256	-0.220	0.036
t-stat	*-7.22*	*-5.10*	*-8.54*	*-8.76*	*-6.16*	*1.06*
MB3	-0.137	-0.156	-0.157	-0.199	-0.159	0.021
t-stat	*-5.79*	*-6.61*	*-7.36*	*-6.13*	*-4.27*	*0.56*
MB4	-0.103	-0.128	-0.155	-0.148	-0.077	-0.027
t-stat	*-4.31*	*-5.20*	*-6.23*	*-5.28*	*-1.74*	*-0.54*
Growth	-0.059	-0.056	-0.050	-0.018	0.021	-0.080
t-stat	*-2.68*	*-3.00*	*-2.20*	*-0.63*	*0.39*	*-1.19*
V-G	-0.154	-0.243	-0.247	-0.269	-0.339	-0.184
t(V-G)	*-6.06*	*-7.07*	*-6.29*	*-6.29*	*-6.82*	*-3.73*

Table 23A. Value Effect and Idiosyncratic Volatility Discount during Earnings Announcements

The table reports, across five-by-five sorts on market-to-book and idiosyncratic volatility, cumulative abnormal returns (CARs) calculated in the three days around earnings announcement dates (the day before, the day of, and the day after the announcement). Announcement dates are from Compustat quarterly file. CARs are from alphas plus residuals from the CAPM fitted to daily returns in the month preceding the earnings announcement. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The portfolios are sorted independently using NYSE (`exchcd`=1) breakpoints. The IVol (market-to-book) portfolios are rebalanced monthly (annually). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Value-Weighted CARs

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	0.165	0.157	0.216	0.152	0.270	-0.104
t-stat	*4.40*	*4.08*	*4.72*	*3.92*	*6.76*	*-1.77*
MB2	0.171	0.124	0.137	0.104	0.120	0.043
t-stat	*4.35*	*3.43*	*3.91*	*2.81*	*3.19*	*0.95*
MB3	0.098	0.094	0.155	0.225	0.224	-0.111
t-stat	*2.70*	*2.64*	*4.49*	*5.71*	*5.17*	*-1.89*
MB4	0.037	0.115	0.136	0.170	0.055	-0.012
t-stat	*1.24*	*3.66*	*4.49*	*5.35*	*1.64*	*-0.30*
Growth	0.086	0.096	0.130	0.111	0.041	0.044
t-stat	*3.35*	*3.53*	*4.27*	*3.06*	*0.93*	*0.85*
V-G	0.069	0.048	0.085	0.036	0.229	0.157
t(V-G)	*1.59*	*0.99*	*1.60*	*0.65*	*3.76*	*2.06*

Panel B. Equal-Weighted CARs

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Value	0.244	0.250	0.282	0.289	0.352	-0.114
t-stat	*8.97*	*8.17*	*9.48*	*11.70*	*9.42*	*-3.44*
MB2	0.174	0.159	0.148	0.173	0.184	-0.014
t-stat	*6.66*	*6.16*	*6.06*	*7.28*	*5.30*	*-0.39*
MB3	0.157	0.177	0.153	0.187	0.107	0.064
t-stat	*6.06*	*7.18*	*6.13*	*7.13*	*3.60*	*1.77*
MB4	0.104	0.166	0.122	0.113	0.021	0.090
t-stat	*4.69*	*7.13*	*6.12*	*5.28*	*0.57*	*2.07*
Growth	0.094	0.103	0.135	0.071	-0.102	0.199
t-stat	*5.87*	*6.13*	*5.34*	*2.92*	*-2.61*	*4.67*
V-G	0.139	0.146	0.147	0.215	0.455	0.315
t(V-G)	*4.49*	*4.59*	*3.69*	*6.93*	*10.19*	*6.63*

Table 24A. Idiosyncratic Volatility Discount: Behavioral Stories

The table presents the IVol discount (IVol) across the limits-to-arbitrage quintiles. RI is residual IO, defined as the residual from the logistic regression of IO on log size and its square. Sh is the probability to be on special, defined in Data Appendix. IVol is defined as the difference in returns between extreme IVol quintiles. We form all quintiles using NYSE breakpoints. The sorts on IVol are performed separately within each limits to arbitrage quintile. The abnormal returns are from the CAPM and the volatility factor model with the market factor, FVIX, and FIVol. For the volatility factor model, we also report the FVIX and FIVol betas. The FVIX and FIVol factors are defined in the heading of Table 1. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Residual Institutional Ownership

	Low	**RI 2**	**RI 3**	**RI 4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	1.175	0.976	0.496	0.398	0.484	0.691
t-stat	*3.77*	*3.09*	*1.90*	*1.87*	*1.92*	*2.41*
$\boldsymbol{\alpha}_{FF3}$	0.993	0.741	0.283	0.289	0.427	0.566
t-stat	*3.46*	*3.10*	*1.42*	*1.59*	*1.97*	*2.06*
$\boldsymbol{\alpha}_{VolF}$	0.184	-0.017	-0.297	-0.086	-0.065	0.249
t-stat	*0.46*	*-0.05*	*-1.14*	*-0.44*	*-0.24*	*0.76*
$\boldsymbol{\beta}_{FVIX}$	-2.258	-2.066	-1.662	-1.309	-1.618	-0.640
t-stat	*-3.83*	*-3.63*	*-3.92*	*-4.22*	*-4.07*	*-2.45*
$\boldsymbol{\beta}_{FIVol}$	0.054	-0.037	-0.014	0.115	0.163	-0.109
t-stat	*0.78*	*-0.47*	*-0.27*	*1.65*	*2.99*	*-1.87*

Panel B. Probability to Be on Special

	Low	**Sh 2**	**Sh 3**	**Sh 4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	0.379	0.108	0.415	0.748	1.210	0.831
t-stat	*1.79*	*0.40*	*1.45*	*2.45*	*3.17*	*2.44*
$\boldsymbol{\alpha}_{FF3}$	0.288	-0.132	0.223	0.464	0.880	0.592
t-stat	*1.44*	*-0.60*	*0.99*	*1.73*	*2.96*	*2.00*
$\boldsymbol{\alpha}_{VolF}$	-0.080	-0.840	-0.513	-0.385	-0.061	0.019
t-stat	*-0.38*	*-2.41*	*-1.76*	*-1.02*	*-0.15*	*0.05*
$\boldsymbol{\beta}_{FVIX}$	-1.132	-1.762	-1.809	-2.037	-2.280	-1.148
t-stat	*-5.04*	*-2.88*	*-4.43*	*-3.97*	*-3.74*	*-2.18*
$\boldsymbol{\beta}_{FIVol}$	0.046	-0.099	-0.074	-0.155	-0.179	-0.225
t-stat	*1.03*	*-1.79*	*-1.14*	*-2.73*	*-2.01*	*-2.85*

Table 25A. Value Effect: Behavioral Stories

The table presents the value effect across the limits-to-arbitrage quintiles. RI is residual IO, defined as the residual from the logistic regression of IO on log size and its square. Sh is the probability to be on special, defined in Data Appendix. The value effect is defined as the difference in returns between extreme market-to-book quintiles. We form all quintiles using NYSE breakpoints. The sorts on market-to-book are performed separately within each limits to arbitrage quintile. The abnormal returns are from the CAPM and the volatility factor model with the market-factor, FVIX, and FIVol. For the volatility factor model, we also report the FVIX and FIVol betas. The FVIX and FIVol factors are defined in the heading of Table 1. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Residual Institutional Ownership

	Low	**RI 2**	**RI 3**	**RI 4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	1.255	0.838	0.526	0.443	0.498	0.757
t-stat	*4.01*	*2.80*	*2.13*	*2.34*	*1.93*	*2.59*
$\boldsymbol{\alpha}_{FF3}$	1.008	0.597	0.308	0.296	0.418	0.590
t-stat	*3.60*	*2.66*	*1.63*	*1.66*	*1.89*	*2.16*
$\boldsymbol{\alpha}_{VolF}$	0.218	-0.143	-0.249	-0.069	-0.089	0.307
t-stat	*0.56*	*-0.46*	*-0.98*	*-0.39*	*-0.32*	*1.01*
$\boldsymbol{\beta}_{FVIX}$	-2.177	-2.053	-1.611	-1.277	-1.671	-0.505
t-stat	*-4.30*	*-3.85*	*-4.00*	*-5.56*	*-4.22*	*-2.13*
$\boldsymbol{\beta}_{FIVol}$	-0.015	-0.032	-0.018	0.079	0.153	-0.168
t-stat	*-0.25*	*-0.45*	*-0.41*	*1.77*	*3.49*	*-2.57*

Panel B. Probability to Be on Special

	Low	**Sh 2**	**Sh 3**	**Sh 4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	-0.033	0.010	0.223	0.622	0.965	0.998
t-stat	*-0.13*	*0.03*	*0.74*	*1.63*	*2.42*	*3.02*
$\boldsymbol{\alpha}_{FF3}$	-0.267	-0.257	-0.058	0.195	0.513	0.780
t-stat	*-1.27*	*-1.10*	*-0.23*	*0.71*	*2.07*	*2.72*
$\boldsymbol{\alpha}_{VolF}$	-0.428	-0.520	-0.278	-0.366	-0.171	0.257
t-stat	*-1.62*	*-1.97*	*-0.92*	*-1.06*	*-0.51*	*0.93*
$\boldsymbol{\beta}_{FVIX}$	-0.322	-0.308	-0.329	-1.071	-1.093	-0.771
t-stat	*-1.85*	*-1.40*	*-1.14*	*-3.09*	*-2.52*	*-2.36*
$\boldsymbol{\beta}_{FIVol}$	-0.199	-0.330	-0.293	-0.410	-0.523	-0.324
t-stat	*-6.98*	*-5.10*	*-5.54*	*-3.97*	*-6.07*	*-4.03*

Table 26A. Arbitrage Asymmetry and the Idiosyncratic Volatility Discount

The table presents the value-weighted CAPM alphas (Panel A), alphas from the volatility factor model with the market factor, FVIX and FIVol (Panel B), and FVIX and FIVol betas from the volatility factor model (Panels C and D, respectively) for 25 portfolios sorted on IVol and Stambaugh et al. (2015) mispricing measure. Idiosyncratic volatility is defined as the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). The definition of the Stambaugh et al. mispricing measure is in the Data section. The portfolios are sorted independently using NYSE (`exchcd`=1) breakpoints. The IVol and mispricing portfolios are rebalanced monthly. The FVIX and FIVol betas estimates are from the volatility factor model with the market factor, FVIX and FIVol. FVIX (FIVol) is the aggregate (idiosyncratic) volatility risk factor that tracks innovations to VIX ($\overline{IVOL}$). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. CAPM Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Under	0.247	0.289	0.270	0.558	0.239	0.008
t-stat	*1.99*	*2.35*	*1.83*	*3.80*	*1.21*	*0.03*
Quint2	0.316	0.356	0.124	0.216	0.117	0.200
t-stat	*2.33*	*2.35*	*0.86*	*1.40*	*0.52*	*0.63*
Quint3	0.376	0.322	-0.040	-0.207	-0.113	0.489
t-stat	*2.26*	*2.28*	*-0.25*	*-1.11*	*-0.66*	*1.86*
Quint4	0.335	0.121	-0.106	-0.162	-0.290	0.625
t-stat	*2.11*	*0.76*	*-0.70*	*-0.93*	*-1.19*	*2.42*
Over	0.160	0.078	-0.242	-0.889	-1.389	1.549
t-stat	*0.66*	*0.39*	*-1.38*	*-4.31*	*-5.53*	*4.08*
O-U	0.087	0.211	0.512	1.447	1.628	1.542
t(O-U)	*0.36*	*0.93*	*2.10*	*5.38*	*5.81*	*4.28*

Panel B. Volatility Factor Model Alphas

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**L-H**
Under	0.012	0.044	0.242	0.693	0.640	-0.628
t-stat	*0.10*	*0.31*	*1.63*	*4.11*	*2.76*	*-2.08*
Quint2	-0.034	0.024	0.025	0.268	0.622	-0.656
t-stat	*-0.31*	*0.15*	*0.14*	*2.05*	*2.43*	*-2.04*
Quint3	0.199	0.177	-0.136	-0.234	0.289	-0.091
t-stat	*1.10*	*1.08*	*-0.73*	*-1.22*	*1.53*	*-0.37*
Quint4	-0.038	-0.139	-0.408	-0.399	0.140	-0.177
t-stat	*-0.25*	*-0.78*	*-2.83*	*-2.41*	*0.42*	*-0.47*
Over	-0.429	-0.172	-0.355	-0.889	-0.775	0.345
t-stat	*-2.19*	*-0.84*	*-1.84*	*-4.28*	*-3.20*	*1.20*
O-U	0.441	0.216	0.596	1.581	1.415	0.973
t(O-U)	*1.98*	*0.90*	*2.47*	*5.60*	*4.76*	*2.91*

Panel C. FVIX Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Under	-0.580	-0.515	-0.057	0.267	0.793	-1.373
t-stat	*-3.80*	*-4.36*	*-0.31*	*2.07*	*3.15*	*-3.89*
Quint2	-0.676	-0.447	-0.071	0.285	1.091	-1.767
t-stat	*-4.07*	*-2.49*	*-0.38*	*2.36*	*4.73*	*-5.07*
Quint3	-0.387	-0.250	-0.030	0.191	1.043	-1.430
t-stat	*-2.75*	*-1.35*	*-0.14*	*1.00*	*3.83*	*-4.33*
Quint4	-0.520	-0.303	-0.172	-0.017	1.151	-1.670
t-stat	*-3.15*	*-1.84*	*-1.13*	*-0.10*	*3.70*	*-3.87*
Over	-0.810	-0.189	0.112	0.414	1.523	-2.333
t-stat	*-6.11*	*-1.25*	*0.47*	*2.18*	*4.19*	*-5.34*
O-U	0.230	-0.326	-0.169	-0.148	-0.730	-0.960
t(O-U)	*1.36*	*-2.03*	*-0.59*	*-0.72*	*-2.78*	*-4.35*

Panel D. FIVol Betas

	Low	IVol2	IVol3	IVol4	High	L-H
Under	0.027	-0.006	-0.002	0.009	0.028	0.000
t-stat	*1.04*	*-0.24*	*-0.06*	*0.26*	*0.89*	*-0.01*
Quint2	-0.031	-0.103	-0.055	-0.065	0.001	-0.032
t-stat	*-1.24*	*-3.66*	*-2.30*	*-1.71*	*0.01*	*-0.67*
Quint3	0.002	-0.024	-0.068	-0.095	-0.066	0.068
t-stat	*0.05*	*-0.68*	*-2.69*	*-2.75*	*-2.45*	*1.52*
Quint4	-0.109	-0.099	-0.182	-0.188	-0.084	-0.025
t-stat	*-3.03*	*-4.38*	*-5.54*	*-6.36*	*-1.55*	*-0.35*
Over	-0.176	-0.134	-0.135	-0.157	-0.074	-0.102
t-stat	*-4.61*	*-3.67*	*-5.46*	*-3.26*	*-1.04*	*-1.38*
O-U	0.203	0.128	0.133	0.166	0.102	-0.102
t(O-U)	*4.47*	*3.07*	*3.63*	*2.25*	*1.33*	*-1.48*