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

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Abstract

This document collects the robustness checks for the paper "Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns". We start with checking the robustness of the idiosyncratic volatility discount (brought into question by Fu (2009) and Huang et al. (2010)). We then consider two alternative way to confirm that high idiosyncratic volatility firms and growth firms perform relatively better in bad times: we look at their conditional CAPM betas and we use the change in VIX instead of the FVIX factor (which mimics the change in VIX). We also check the robustness of the results in the paper to two modifications of the FVIX factor: the tradable version that uses expanding window factor-mimicking regression instead of the one full-sample factor-mimicking regression and the version that uses only the data from 1990 on, to get rid of the outliers in 1987. Lastly, we consider the alternative volatility risk factors of Adrian and Rosenberg (2008) and Chen and Petkova (2012) and their relation to the volatiluty risk factors we use.

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

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 volatility and short in high 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 the last 23 years data, 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). This 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.

The ICAPM alphas of the low minus high volatility portfolio are insignificant in all periods, suggesting that after controlling for aggregate volatility risk, it is not necessary to appeal to the short term reversal as an explanation of the idiosyncratic volatility discount, because aggregate volatility risk does the job alone.

Table 2A also reports the FVIX betas from the ICAPM 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, and that, controlling for the FVIX factor, the short term reversal story is not necessary to explain the idiosyncratic volatility discount.

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

Barinov (2008) develops a comparative statics model similar to Johnson (2004) to show that disagreement can be replaced by idiosyncratic volatility and leverage (the source of convexity in the Johnson model) can be replaced by growth options. 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 the link between the value effect and idiosyncratic volatility.

Therefore, we expect that the beta of the HML, HMLh, IVol, and IVolh portfolios (see the portfolio definitions in the paper) will increase in recessions, and the 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 3A, 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

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

Since the data on the four business cycle variables are available for a long period of time, the sample period in Table 3A 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

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

and define the conditional beta as

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

The left part of Table 3A 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 3A, 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 4A runs the horse race between the conditional CAPM and the three-factor ICAPM with FVIX and FIVol from the paper. The first five columns largely reproduce the ICAPM results and conditional CAPM results from the paper, which will serve as the benchmark for the horse race. Comparing the conditional CAPM with ICAPM, 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 ICAPM 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 ICAPM" alpha is within a few bps of the ICAPM 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 it starts significant in the ICAPM 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 The Three Idiosyncratic Volatility Effects and Exposure to Changes in VIX

The previous sections show that exploiting the idiosyncratic volatility discount and the value effect means extreme negative exposure to the FVIX factor. Because FVIX is the portfolio with the maximum positive correlation with changes in expected aggregate volatility (the VIX index), the negative loadings means 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 much 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 test the hypothesis that low volatility firms and value firms react more negatively to aggregate volatility increases than high volatility firms and growth firms using the change in VIX directly. 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 Table 5A, we report the slopes on the VIX change ($\beta_{\Delta VIX}$)in the regression of the arbitrage portfolios returns on the market factor and the 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 the change in VIX is replaced by the 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 5A 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 indeed 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, in contrast, 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 5A, 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 4 in the paper 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 5A 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 5A 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 the change in VIX is a noisy measure of unexpected changes in expected aggregate volatility, and low values of the 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 5A, 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 5A 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 negative alphas of the value minus growth and the low minus high volatility strategies. The negative loadings of these strategies on the change in VIX help to explain the negative CAPM alphas by pointing out that the negative market betas severely overstate their performance 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.

Overall, in Table 5A we are able to use daily changes in VIX and to reconfirm the conclusions from 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.

4 Modifications of the FVIX Factor

4.1 Tradable FVIX: Is There a Look-Ahead Bias in FVIX?

When we construct the FVIX factor - the portfolio that mimics the daily changes in VIX - we run one regression using all available observations. 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 the excess returns to the six size and book-to-market portfolios using the data from 1986 to 2008. 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, investors had an idea about what current expected aggregate volatility and its change were long before the VIX index became available. 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 2008. (Notice, however, that we cannot backfill FVIX values to pre-1986 years

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 the daily change in VIX on the excess returns to the six size and book-to-market portfolios using only the past available information. That is, if we need the weights of the six size and book-to-market portfolios 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 six size and book-to-market portfolios 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.

In Panel A of Table 6A, we compare FVIX and FVIXT using the sample from January 1991 to December 2008. We set aside the first five years (1986-1990) as the learning sample - the investors and the econometrician learn how to mimic the changes in VIX using these first five years of data.

First of all, Panel A shows that FVIX and FVIXT are very similar to each other. The correlation between them (see the last column of Panel A) is 0.946. The correlation between FVIXT and the change in VIX is 0.646, whereas the correlation between FVIX and the change in VIX is 0.684. FVIX comes closer to mimicking the change in VIX, because it uses superior information, but the difference is not large.

Second, the in 1991-2008 sample, we find that the factor premium of FVIXT is even larger than the factor premium of FVIX: the average raw return (the CAPM alpha) of FVIX is -88.4 per month, t-statistic -2.33 (-33.2 bp per month, t-statistic -2.08), versus the average raw return (the CAPM alpha) of FVIXT of -157.5 bp per month, t-statistic -3.04 (-90 bp per month, t-statistic -2.61). The average return and the CAPM alpha of FVIXT do look extreme, but they are also expectedly noisier.

In Panels B and C of Table 6A, we reestimate the ICAPM for the nine arbitrage portfolios used throughout this section replacing FVIX by FVIXT and using the sample from January 1991 to December 2008. If the results in the previous sections are not influenced by the look-ahead bias, the ICAPM with FVIXT in 1991-2008 should produce the same alphas as the ICAPM with FVIX in 1991-2008. The FVIXT betas should be about twice smaller than FVIX betas in 1991-2008, because the factor premium of FVIXT is twice larger than the factor premium of FVIX.

In the first column of Panels B and C, we report the CAPM alphas in 1991-2008. We find that the anomalies we discuss in this paper are still there in the shorter sample, and most of the alphas of the nine arbitrage portfolios are significant. 11 out of the 17 alphas are significant at 5% level and two more are significant at the 10% level. The CAPM alphas hover around 1% per month, in some instances climbing as high as 1.5% per month. The CAPM alphas in 1991-2008 are quite close to the CAPM alphas in 1986-2006, hence FVIXT has the same distance to go as FVIX in the rest of the paper.

In the second column of Panels B and C, we report the alphas from the ICAPM with FVIX. Just as in the full sample, the vast majority of the alphas become insignificant after we control for FVIX, and the ones that remain significant, are reduced by 25-50%. The importance of FVIX in explaining the anomalies is further confirmed by the FVIX betas in the third column. The FVIX betas are always highly significant and are close to their full-sample values.

In the fourth column of Panels B and C, we show that FVIXT works even better than FVIX. For the 17 portfolios in Panels B and C, the two-factor ICAPM with FVIX produces five significant alphas (versus 11 significant CAPM alphas), and the two-factor ICAPM with FVIXT produces only two significant alphas. In the fifth column of Panels B and C, we report the FVIXT betas of the nine anomalous portfolios and find that all FVIXT betas are sizeable, negative, and significant, just as the respective FVIX betas in the rest of the paper. The magnitude of the FVIXT betas is indeed twice smaller than the magnitude of the FVIX betas, reflecting the difference in the factor risk premiums.

We conclude therefore that the results in the paper are not contaminated by the potential look-ahead bias in FVIX. We can achieve very similar results using the fully tradable version of FVIX 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 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.

4.2 FVIX90: The Impact of the October 1987

One reason why dropping the first five years from the sample can be desirable is the existence of the October 1987 outlier. On October 19, 1987, the market dropped by about 20% and the VIX spiked to all-time high of 150.19, staying above 95 for a week thereafter (for comparison, the highest value of VIX during the recent financial crisis was 87.24 on November 20, 2008). However, the October 1987 market crash did not develop into an economy-wide recession. By the end of 1987, VIX declined into mid-to-high 30s, and the market logged a positive return for 1987, since the crash came on the heels of rather quick market growth.

Since we use a full-sample regression to create FVIX, one concern can be that October 1987 remains in the sample forever and can change the coefficients in the factor-mimicking regression. To check the robustness of our results, we try forming FVIX using the regression that uses only the data between January 1991 and December 2008.

In the last row of Panel A of Table 6A, we find that this version of FVIX (we refer to it as FVIX90) is similar to the all-sample version of FVIX. The correlation between FVIX and FVIX90 is 0.994. FVIX and FVIX90 also have very similar correlations with the change in VIX during the 1991-2008 period - the correlations are 0.684 and 0.692, respectively.

Looking at the factor risk premiums, we find that FVIX90 is somewhat cleaner than FVIX due to the removal of the October 1987 outlier. The CAPM alpha of FVIX in 1991-2008 is -33.2 bp per month, t-statistic 2.08, whereas the CAPM alpha of FVIX90 is -24.6 bp per month, t-statistic -2.31. Similarly, the Fama-French alpha of FVIX is -32.7 bp per month, t-statistic -1.81, versus -28.6 bp per month, t-statistic -2.34, for FVIX90.

In the two leftmost columns of Panels B and C, we report the ICAPM alphas and FVIX90 from the two-factor ICAPM with the market factor and FVIX90 (instead of FVIX). As discussed earlier, we start with 11 CAPM alphas significant at the 5% level and two more CAPM alphas significant at the 10% level. In the ICAPM with the market factor and FVIX, five alphas stay significant at the 5% level (but are halved in magnitude compared to the CAPM alphas) and two more stay significant at the 10% level. In the ICAPM with FVIX90, only three alphas stay significant at the 5% level (one of them marginally significant with t-statistic 1.99) and two more stay significant at the 10% level. In all 17 cases, the ICAPM with FVIX90 produces larger improvement in alphas than the ICAPM with FVIX in the same sample period, and in most cases the FVIX90 betas are larger. We conclude that excluding the October 1987 outlier indeed improves the performance of the FVIX factor.

4.3 Alternative Measures of Volatility Risk

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 three-factor ICAPM with the market factor and the two innovations has better fit than alternative asset-pricing models.

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.[1] 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 Table 7A, we compare the performance of several models: the three-factor ICAPM with FVIX and FIVol, the three-factor ICAPM of Adrian and Rosenberg (2008), the two-factor ICAPM with the average volatility factor, motivated by Chen and Petkova (2012), as well as Adrian and Rosenberg (2008) and Chen and Petkova (2012) models augmented with FVIX, FIVol, or both.

Panel A looks at the alphas of the five arbitrage portfolios we considered in Tables 3A-6A. The first two columns (columns zero and one) reproduce the two columns of Table 4 in the paper and report the alphas from the CAPM and the three-factor ICAPM with FVIX and FIVol. On average, ICAPM 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 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 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 CAPM alphas. Overall, Panel A 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.

Column six looks at the alphas from the ICAPM with the market factor and the factor-mimicking portfolio for the innovations to average volatility.[2] Somewhat unexpectedly, we

[1] Average total volatility is the average total (systematic and non-systematic) volatility of all individual stocks.

[2] We thank Ralitsa Petkova for sharing the innovation series.

find that the average volatility 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 three and five 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 7A 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 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.

In Panels B of Table 7A, we look at the volatility risk betas from the models described above. We come to four 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 have the "wrong" sign - i.e., the sign that would make their alphas 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.

Third, contrary to Chen and Petkova, Model 6 finds no evidence that arbitrage portfolios capturing the idiosyncratic volatility discount load on the AV factor, but we do find that 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. Fourth, in Model 7 with AV, FVIX, and FIVol factors 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.

5 Profitability Effect and Aggregate Volatility Risk

5.1 RMW Factor and Aggregate Volatility Risk

Barinov (2015) analyzes the overlap between the profitability effect of Haugen and Baker (1996) and Novy-Marx (2013), which is the basis of the Fama and French (2015) new RMW factor. Barinov (2015) 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 8A reproduces Table 2 from Barinov (2015) in slightly longer sample. Panel A reports the alphas of RWM 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 find 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 8A 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 8A 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 (2015).

5.2 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 three-factor ICAPM with the market factor, FVIX and FIVol is derived from our theoretical model.

However, Table 9A 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 reports that FVIX is nearly orthogonal to the momentum factor. In the first column of Table 9A, 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 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 three-factor ICAPM (MKT, FVIX, FIVol), 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 9A, FVIX betas of all low-minus-high 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 three-factor ICAPM (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 9A are about 60% of similar betas in the three-factor ICAPM (see Table 4 in the paper), but the FVIX beta of IVol IO and HML IO portfolios in column three of Table 9A 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 three-factor ICAPM with the market factor, FVIX, and FIVol.

Column five of Table 9A 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 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. The alphas reveal a strong overlap between RMW and FVIX, as in Barinov (2015) and Table 8A. When we add FVIX and FIVol to the three-factor Fama-French model, the alpha 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 8A.

Columns 13 and 14 report the alphas from the five-factor Fama-French 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 10% level. However, this is still behind column two (the three-factor Fama-French model augmented with FVIX and FIVol) and the three-factor ICAPM (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.

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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 (ICAPM). 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*
$\boldsymbol{\alpha}_{ICAPM}$	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. 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 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 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_{MKT}^{Rec}	β_{MKT}^{Exp}	$\beta_{MKT}^{Rec}-\beta_{MKT}^{Exp}$	β_{MKT}^{Rec}	β_{MKT}^{Exp}	$\beta_{MKT}^{Rec}-\beta_{MKT}^{Exp}$
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 4A. 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 3A. The models fitted to returns of the arbitrage assets are the CAPM, the Conditional CAPM, the three-factor ICAPM (the market factor, FVIX, and FIVol), and the Conditional CAPM augmented with FVIX and FIVol (C-ICAPM). 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_{ICAPM}	β_{FVIX}	β_{FIVol}	$\alpha_{C-ICAPM}$	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 5A. 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 3A. The sensitivity is measured by estimating the following regressions:

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta_{\Delta VIX}} \cdot \Delta VIX \tag{7}$$

$$Ret = \alpha + \beta_{MKT} \cdot MKT + \boldsymbol{\beta_{FVIX}} \cdot FVIX \tag{8}$$

$\boldsymbol{\beta}_{MKT}$ is from the CAPM fitted to the daily data. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2008.

Value-Weighted				Equal-Weighted			
	$\boldsymbol{\beta}_{\Delta VIX}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{MKT}$		$\boldsymbol{\beta}_{\Delta VIX}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{MKT}$
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*

Table 6A. Value Effect, Idiosyncratic Volatility Discount, and the Tradable Version of FVIX

Panel A compares the FVIX factor with its tradable version (FVIXT), for which the weights in the factor-mimicking portfolio are estimated using only past information, and the FVIX90 factor that is estimated using only the data from January 1990 onward. We report the correlations of FVIX, FVIXT and FVIX90 with the change in VIX ($Corr(\Delta VIX, \cdot)$) and the correlation between FVIX and either FVIXT or FVIX90 ($Corr(FVIX, \cdot)$), as well as the average monthly returns, the CAPM alphas, and the Fama-French alphas of all three factors.

Panel B and Panel C report, respectively, the value-weighted and equal-weighted CAPM alphas, ICAPM alphas and FVIX betas of the nine anomalous portfolios described in the heading of Table 3A. The ICAPM alphas and FVIX betas are estimated three ways: using the conventional FVIX factor (α_{ICAPM} and β_{FVIX}), using the tradable FVIX factor (α_{ICAPMT} and β_{FVIXT}), and using the FVIX factor estimated from January 1990 onward ($\alpha_{ICAPM90}$ and β_{FVIX90}). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1991 to December 2008.

Panel A. FVIX versus Tradable FVIX versus FVIX90

	$Corr(\Delta VIX, \cdot)$	Return	α_{CAPM}	α_{FF}	$Corr(FVIX, \cdot)$
FVIX	0.684	-0.884	-0.332	-0.327	
t-stat	*13.7*	*-2.33*	*-2.08*	*-1.81*	
FVIXT	0.646	-1.575	-0.900	-0.605	0.946
t-stat	*12.4*	*-3.04*	*-2.61*	*-1.77*	*42.6*
FVIX90	0.692	-0.704	-0.246	-0.286	0.994
t-stat	*14.0*	*-2.27*	*-2.31*	*-2.34*	*133.0*

Panel B. Value-Weighted Returns

	α_{CAPM}	α_{ICAPM}	β_{FVIX}	α_{ICAPMT}	β_{FVIXT}	$\alpha_{ICAPM90}$	β_{FVIX90}
HML	0.541	0.329	-0.638	0.063	-0.531	0.266	-0.863
t-stat	*2.04*	*1.51*	*-2.74*	*0.32*	*-4.29*	*1.20*	*-2.31*
IVol	0.846	0.277	-1.715	0.148	-0.776	0.048	-2.500
t-stat	*2.64*	*1.31*	*-8.33*	*0.47*	*-4.52*	*0.22*	*-7.52*
IVolh	0.766	0.104	-1.996	-0.052	-0.909	-0.166	-2.923
t-stat	*1.83*	*0.32*	*-9.79*	*-0.12*	*-5.09*	*-0.50*	*-8.80*
HMLh	1.036	0.764	-0.821	0.457	-0.643	0.671	-1.144
t-stat	*2.49*	*2.00*	*-4.44*	*1.31*	*-5.53*	*1.73*	*-3.80*
IVol55	-0.416	0.059	1.430	0.242	0.731	0.233	2.033
t-stat	*-1.25*	*0.22*	*10.6*	*0.78*	*5.81*	*0.83*	*9.05*
IVol IO	1.313	0.641	-2.026	0.413	-0.999	0.364	-2.975
t-stat	*2.75*	*1.87*	*-6.60*	*1.08*	*-4.20*	*1.12*	*-6.10*
IVol Sh	1.318	0.598	-2.170	0.270	-1.164	0.300	-3.190
t-stat	*2.56*	*1.57*	*-5.17*	*0.61*	*-4.17*	*0.82*	*-4.81*
HML IO	0.810	0.476	-1.009	0.134	-0.751	0.331	-1.503
t-stat	*1.41*	*0.93*	*-2.45*	*0.28*	*-3.67*	*0.66*	*-2.44*
HML Sh	1.679	1.228	-1.359	0.819	-0.956	1.053	-1.963
t-stat	*2.90*	*2.38*	*-2.78*	*1.72*	*-3.72*	*1.99*	*-2.61*

Panel C. Equal-Weighted Returns

	α_{CAPM}	α_{ICAPM}	β_{FVIX}	α_{ICAPMT}	β_{FVIXT}	$\alpha_{ICAPM90}$	β_{FVIX90}
IVol	0.509	-0.027	-1.615	-0.112	-0.689	-0.255	-2.395
t-stat	*1.39*	*-0.09*	*-6.63*	*-0.27*	*-3.58*	*-0.76*	*-6.30*
IVolh	0.925	0.169	-2.279	0.016	-1.010	-0.142	-3.346
t-stat	*1.94*	*0.48*	*-6.17*	*0.03*	*-3.62*	*-0.38*	*-5.73*
HMLh	1.874	1.592	-0.850	1.391	-0.536	1.498	-1.180
t-stat	*4.71*	*4.49*	*-3.12*	*4.04*	*-3.46*	*4.22*	*-2.70*
IVol55	-0.627	0.027	1.973	0.086	0.793	0.275	2.829
t-stat	*-1.52*	*0.08*	*6.96*	*0.18*	*3.55*	*0.72*	*6.31*
IVol IO	0.850	0.184	-2.009	0.038	-0.903	-0.070	-2.885
t-stat	*2.05*	*0.61*	*-7.26*	*0.09*	*-3.88*	*-0.21*	*-6.47*
IVol Sh	1.156	0.569	-1.769	0.391	-0.849	0.319	-2.622
t-stat	*2.89*	*1.67*	*-5.38*	*0.87*	*-3.62*	*0.88*	*-5.06*
HML IO	1.431	0.942	-1.477	0.659	-0.858	0.752	-2.129
t-stat	*2.76*	*2.10*	*-2.93*	*1.42*	*-3.08*	*1.65*	*-2.76*
HML Sh	1.519	1.170	-1.051	0.938	-0.646	1.050	-1.472
t-stat	*3.20*	*2.75*	*-2.57*	*2.21*	*-2.90*	*2.38*	*-2.31*

Table 7A. 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:

$$Model\ 0 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) \quad (9)$$

$$Model\ 1 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \quad (10)$$

$$Model\ 2 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t \quad (11)$$

$$Model\ 3 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FVIX} \cdot FVIX_t \quad (12)$$

$$Model\ 4 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FIVol} \cdot FIVol_t \quad (13)$$

$$Model\ 5 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \quad (14)$$

$$Model\ 6 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{AV} \cdot AV_t \quad (15)$$

$$Model\ 7 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{AV} \cdot AV_t + \beta_{FVIX} \cdot FVIX_t + \beta_{FIVol} \cdot FIVol_t \quad (16)$$

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 8A. 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	ICAPM	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 9A. 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 3A. 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*