Stocks with Extreme Past Returns: Lotteries or Insurance?

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Abstract

The paper shows that lottery-like stocks are hedges against unexpected increases in market volatility. The loading on the aggregate volatility risk factor explains the majority of low abnormal returns to stocks with high maximum returns in the past month (Bali, Cakici, and Whitelaw, 2011) and high expected skewness (Boyer, Mitton, and Vorkink, 2010). Aggregate volatility risk also explains the new evidence that the maximum effect and the skewness effect are stronger for firms with high market-to-book or high expected probability of bankruptcy.

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1 Introduction

Recent research has established that stocks with lottery-like payoffs, i.e., stocks that offer a small chance of a huge payoff, earn low returns going forward. Boyer, Mitton, and Vorkink (2010) document a negative association between individual firm skewness and future returns, and Bali, Cakici, and Whitelaw (2011) establish a similar relation between extreme positive returns in the past month and expected returns in the next month.

The theoretical argument behind the tendency of lottery-like stocks to have low future returns is developed in Barberis and Huang (2008), Brunnermeier and Parker (2005), and Mitton and Vorkink (2007), among others. Mitton and Vorkink introduce in their model "lotto investors" with explicit skewness preference, who bid up the prices of lottery-like stocks. Barberis and Huang develop a model with prospect theory utility and show that the preference for lottery-like stocks arises from the tendency to overestimate the probability of the large gain observed in psychological experiments. Barberis and Huang show that prospect-utility investors value lottery-like stocks more highly than expected-utility investors. Brunnermeier and Parker argue that the overestimation of the probability of rare positive events results from the attempt to choose the optimal set of beliefs to maximize the current felicity. The agents in Brunnermeier and Parker trade off the costs of holding biased beliefs with the gains from believing in what makes them happier. The trade-off results in an internal solution with overvaluation of lottery-like stocks (from the point of view of an investor with unbiased beliefs).

This paper offers a rational explanation for why lottery-like stocks have low expected returns by pointing out that such stocks tend to act as valuable insurance against unexpected increases in market volatility. Lottery-like stocks tend to be growth stocks with high idiosyncratic volatility, and, as Barinov (2011, 2013) shows, such stocks are hedges against aggregate volatility risk. Thus, lottery-like stocks should also be hedges against aggregate volatility risk.

The reason why growth firms with high idiosyncratic volatility, and lottery-like stocks in particular, are hedges against aggregate volatility risk, is two-fold. First, growth options, as any option, react positively to increases in volatility, holding everything else fixed, as Grullon, Lyandres, and Zhdanov (2012) show. As Barinov (2013), Duarte et al. (2012), and Herskovic et al. (2016) document, idiosyncratic volatility has a strong common component that comoves significantly with market volatility. Hence, the favorable reaction of growth options to increases in firm-level volatility implies that they will do well when aggregate volatility increases. This effect will naturally be stronger for volatile firms, because such firms tend to see larger absolute increases in firm-level volatility.

Second, as Johnson (2004) proves, higher volatility of the underlying asset makes the option less sensitive to the changes in its value and therefore, less risky. The comovement between firm-level volatility and market volatility together with the Johnson result implies that when market volatility and market risk premium go up, betas of growth options will go down due to an increase in the volatility of the underlying asset. Thus, growth options will suffer a smaller price drop due to a smaller increase in their risk and discount rate.

The empirical analysis in my paper proceeds as follows. I first show that firms with high extreme returns in the past and firms with large expected idiosyncratic skewness tend to have high idiosyncratic volatility and firm-specific uncertainty, as well as option-like equity, which would be the necessary condition for the aggregate volatility risk explanation. I then form an aggregate volatility risk factor (FVIX factor) by creating an arbitrage portfolio that would mimic daily changes in the VIX index. VIX is implied volatility of the options on the Standard and Poor's S&P 100 index, and thus can be used as a measure of expected aggregate volatility.[1] As Ang, Hodrick, Xing, and Zhang (2006) show, at a daily frequency the autocorrelation of VIX is very close to one, therefore, daily changes in VIX should be a good proxy for innovations to expected aggregate volatility, the state variable of interest in the Intertemporal Capital Asset Pricing Model (ICAPM) context.

I find that FVIX is tightly correlated with the VIX change, earns a significant risk premium, and can predict future volatility, as Chen (2002) suggests a valid aggregate volatility risk factor should do. Most importantly, in quintile sorts the FVIX factor can explain 70-100% of the maximum effect of Bali et al. (2011) and the skewness effect of Boyer et al. (2010). In quintile sorts, these effects stand at around 70 basis points (bp) and 35 bp per month, respectively, prior to controlling for FVIX, and controlling for FVIX reduces them to almost zero. The portfolios of lottery-like stocks (with the most positive skewness or the largest past maximum returns) also exhibit large and positive FVIX betas. Since FVIX is, by construction, positively correlated with unexpected changes in aggregate volatility, the positive betas show that lottery-like stocks beat the benchmark models when VIX goes up and are therefore hedges against aggregate volatility risk.

My hypothesis is that the aggregate volatility risk explanation of low returns to lottery-like stocks works through convexity in firm value. An obvious prediction is that the skewness effect and the maximum effect should be stronger for growth stocks, and this regularity should be explained by aggregate volatility risk. In double sorts, the maximum effect and skewness effect are roughly 60 bp per month greater for growth stocks than for value stocks. Controlling for FVIX, this difference is reduced to about 20 bp per month

[1]The paper uses the old definition of VIX, because it has longer coverage, including October 1987. The new VIX uses options on the S&P 500, and the index used herein is currently called VXO. All results in the paper are robust to using the newer VIX.

irrespective of which model (CAPM, Fama-French, Carhart) I add FVIX to. Also, FVIX betas reveal that growth lottery-like stocks load more positively on FVIX and thus offer a significantly better hedge against aggregate volatility risk than value lottery-like stocks.

By the same token, I predict that the expected returns to lottery-like stocks will be lower and their hedging power against aggregate volatility risk will be greater if the equity of the firm is more option-like due to the existence of risky debt and limited liability. I measure the option-likeness of equity by looking at O-score from Ohlson (1980), which proxies for expected probability of bankruptcy. Firms with a higher O-score are closer to the point where limited liability starts to matter, and their equity is thus more option-like. I find that the maximum effect and the skewness effect are indeed stronger for firms with higher O-score, and the majority of this regularity can be explained by aggregate volatility risk. I also find that lottery-like stocks with higher O-score are better hedges against aggregate volatility risk than lottery-like stocks with lower O-score.

I also consider the minimum effect, which should be symmetric to the maximum effect of Bali et al. (2011). If investors have a preference for positive skewness or lottery-like stocks, they will avoid stocks that have a high probability of a disastrous loss. Thus, sorting firms on the past minimum return should reveal that stocks with the most negative past minimum return have the highest expected returns. However, my explanation of the maximum effect implies the opposite prediction: if the maximum effect exists because past maximum return proxies for idiosyncratic volatility, and idiosyncratic volatility in turn proxies for aggregate volatility risk exposure, past minimum return will also proxy for idiosyncratic volatility and will be negatively related to future returns.

In the data, firms with the most negative past minimum returns earn negative alphas of the same magnitude as firms with the most positive past maximum returns even after I control for past maximum returns in the minimum sorts. This evidence is consistent with my explanation of the maximum effect and inconsistent with the view that low expected returns to firms with high maximum returns are due to lottery preference. I also find that the minimum effect is largely explained by the aggregate volatility risk factor, that the minimum effect is stronger for growth firms and distressed firms, just as the maximum effect is, and that the majority of these regularities can be explained by the FVIX factor.

Lastly, I perform several cross-sectional tests that aim to check whether the variation in FVIX beta is priced if it is unrelated to variation in lottery-likeness and, vice versa, whether the variation in lottery-likeness is priced if it is unrelated to variation in FVIX betas. I perform portfolio-level cross-sectional regressions of future returns on lottery-likeness measures and FVIX beta, as well as standard asset-pricing controls. The regressions suggest that the lottery effects decline by about one-half after controlling for FVIX beta and become statistically insignificant. A similar conclusion emerges in portfolio sorts that sort firms on lottery-likeness measures orthogonalized to FVIX beta and on FVIX beta orthogonalized to lottery-likeness measures. On the other hand, the confidence intervals in both cases include large values of the lottery effects even after controlling for FVIX beta.

In order to improve the precision of the estimates, I re-estimate the same cross-sectional regressions at the firm level. The firm-level regressions, somewhat surprisingly, reveal little overlap between FVIX beta and lottery-likeness measures, even though both seem to be priced. One potential explanation of that is errors-in-variables (the errors are averaged out at the portfolio level). In firm-level regressions, the slopes on both FVIX beta and lottery-likeness measures are three times smaller than in portfolio-level regressions, and the overlap between these variables is also three times smaller. Another possible explanation is that the relation between expected returns and both FVIX beta and lottery-likeness is highly non-linear (in portfolio sorts, expected returns have a slight hump-shape in the bottom four quintiles followed by a sharp drop in the top quintile), and the non-linearity matters more in the richer cross-section of the firm-level regressions. I test the misspecification explanation by replacing the lottery-likeness measures and FVIX beta by the dummy variables for the top quintile and find that under this research design FVIX beta explains 100% of the lottery effects.

2 Data

The main test assets in the paper are quintile portfolios sorted on three variables of interest: the maximum past return (as in Bali et al., 2011), the expected skewness (as in Boyer et al., 2010), and the minimum past return. Stocks with prices below \$5 on the portfolio formation date are excluded. The results in the paper are robust to including stocks priced below \$5 in the sample, as in Bali et al. and Boyer et al.

The maximum past return is the maximum daily return in the past month. The minimum past return is defined in the same way, but is multiplied by -1, so that high values signify large minimum returns. Minimum return is orthogonalized to maximum return by performing, each month, a cross-sectional regression of minimum return on maximum return in the same month and taking the residuals (RMin).

Following Boyer et al. (2010), expected skewness is defined as the expected value from

$$\begin{aligned} ISkew_t = \; & \gamma_0 + \gamma_1 \cdot ISkew_{t-60} + \gamma_2 IVol_{t-60} + \gamma_3 \cdot Mom_{t-60} + \gamma_4 \cdot Turn_{t-60} + \\ & + \gamma_5 \cdot NASD_{t-60} + \gamma_6 \cdot Small_{t-60} + \gamma_7 \cdot Med_{t-60} + \Gamma \cdot IndDum. \end{aligned} \quad (1)$$

The regression is performed in cross-section every month. The left-hand side variable is idiosyncratic skewness (ISkew), computed from daily returns in the past 60 months. The right-hand side includes idiosyncratic volatility (IVol), also computed from daily returns in the past 60 months, cumulative monthly return in the past 12 months excluding the most recent one (Mom), average monthly turnover in the past year (Turn), Nasdaq dummy (NASD), small firms dummy (Small), medium firms dummy (Med), and industry dummies. Detailed definitions of all variables are in Appendix A.

To measure the innovations to expected aggregate volatility, I use daily changes in the old version of the VIX index calculated by CBOE and available from WRDS. Using the old version of VIX provides longer coverage. The VIX index measures the implied volatility of the at-the-money options on the S&P 100 index.

I form a factor-mimicking portfolio that tracks daily changes in the VIX index. I regress daily changes in VIX on daily excess returns to the base assets - five quintile portfolios sorted on past return sensitivity to VIX changes, as in Ang et al. (2006).[2]:

$$\begin{aligned} \Delta VIX_t \; = \; & \underset{(0.019)}{0.058} - \underset{(0.075)}{0.033} \cdot (VIX1_t - RF_t) - \underset{(0.148)}{0.645} \cdot (VIX2_t - RF_t) \\ & - \underset{(0.112)}{0.367} \cdot (VIX3_t - RF_t) - \underset{(0.393)}{0.653} \cdot (VIX4_t - RF_t) \\ & + \underset{(0.137)}{0.163} \cdot (VIX5_t - RF_t), \quad R^2 = 0.511, \end{aligned} \tag{2}$$

where $VIX1_t, \ldots, VIX5_t$ are the VIX sensitivity quintiles described in the next paragraph, with $VIX1_t$ being the quintile with the most negative sensitivity. The fitted part of the regression above less the constant is my aggregate volatility risk factor (FVIX factor).

The return sensitivity to VIX changes ($\gamma_{\Delta VIX}$) I use to form the VIX sensitivity quintiles 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 using daily

[2] The factor-mimicking regression is performed using the full sample to increase the precision of the estimates. In untabulated results, I find that all results in the paper are robust to using an out-of-sample version of FVIX that is estimated using an expanding window.

data (at least 15 non-missing returns are required):

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t. \tag{3}$$

In untabulated results, I find that my results are robust to changing the base assets from the VIX sensitivity quintiles to the ten industry portfolios of Fama and French (1997) or the six size and book-to-market portfolios of Fama and French (1993).

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

$$O = -1.32 - 0.407 \cdot \ln TA + 6.03 \cdot \frac{TL}{TA} - 1.43 \cdot \frac{WC}{TA} + 0.076 \cdot \frac{CL}{CA} - 1.72 \cdot I(TL > TA)$$
$$-2.37 \cdot \frac{NI}{TA} - 1.83 \cdot \frac{FFO}{TA} + 0.285 \cdot I(NI < 0 \; \& \; NI_{-1} < 0) - 0.521 \cdot \frac{NI - NI_{-1}}{|NI| + |NI_{-1}|}, \tag{4}$$

where TA is the book value of total assets (Compustat item at), TL is the book value of total liabilities (lt), WC is working capital (wcap), CL are current liabilities (lct), CA are current assets (act), NI is net income (ni), NI_{-1} is the previous year net income, FFO are funds from operation (pi plus dp), $I(TL > TA)$ is a dummy variable equal to one if the book value of total liabilities exceeds the book value of total assets, and equal to zero otherwise, $I(NI < 0 \; \& \; NI_{-1} < 0)$ is a dummy variable equal to one if the net income was negative in the two most recent years, and equal to zero otherwise. Expected probability of bankruptcy in the next two years, Pr, can be obtained as the logistic transformation of O-score: $Pr = e^O/(1 + e^O)$.

3 Lottery-like stocks and aggregate volatility risk

3.1 FVIX as an ICAPM factor

My aggregate volatility risk explanation of the maximum effect and the skewness effect has two necessary conditions. First, sorting on the maximum past return should also produce a sort on volatility and option-likeness of equity, and thus a sort on the exposure to aggregate volatility risk. Second, the FVIX factor I use to explain the maximum effect should satisfy three requirements for a valid volatility risk factor: it should be significantly correlated with the variable it mimics, it has to earn a significant risk premium, and, as Chen (2002) shows, its return should predict future volatility.

In Table 1, I test these three hypotheses. The left part of Panel A records that the correlation between FVIX and the change in VIX it mimics is quite high at 0.715. On the right side of Panel A, the raw return to FVIX is -1.31% per month, t-statistic -4.27, the CAPM alpha is -45.5 bp per month, t-statistic -4.50, and Fama-French (1993) and Carhart (1997) alphas of FVIX are both at -44 bp per month, t-statistics -3.81 and -3.75.

The negative risk premium to FVIX is to be expected: by construction, FVIX represents the combination of the base assets with the most positive correlation with the change in VIX, and thus the best available hedge against aggregate volatility risk. The return to FVIX then measures what investors are willing to pay for insurance against increases in VIX, and large negative numbers indicate that investors care about such insurance. The negative risk premium of FVIX also indicates that positive FVIX betas signify a hedge against aggregate volatility risk, and vice versa.

Panel B explores the prediction of Chen (2002) that a volatility risk factor should predict future market volatility. To that end, I regress logs of several measures of market volatility – VIX, TARCH(1,1) market volatility forecast,[3] and squared daily market returns as a measure of realized market volatility – on leads and lags of FVIX returns. Panel B reports the slopes of these pairwise regressions, as well as the slope from the probit regression of the NBER recession dummy on leads and lags of FVIX returns. The slopes

[3]Please refer to Appendix A for details about the TARCH(1,1) model.

on the lags measure the ability of FVIX to predict volatility and recessions, the slopes on the leads measure the ability of the volatility measures and the NBER recession dummy to predict FVIX returns.

I find that FVIX can indeed predict future volatility at least one quarter ahead (it can also predict the TARCH volatility forecast and potentially realized volatility and VIX two quarters ahead), as a valid volatility risk factor should. I also find that FVIX returns can predict future recessions (up to one year ahead), and that high FVIX returns coincide in time with high expected and realized volatility. As expected under market efficiency, neither the volatility measures nor the NBER recession dummy can predict FVIX returns.

3.2 Extreme returns, firm-level volatility, and option-likeness of equity

In Table 2, I test the other necessary condition of my explanation of the lottery effects: the hypothesis that lottery firms also have higher firm-level volatility/uncertainty and option-like equity. In Panel A, I look at several measures of firm-specific volatility/uncertainty – idiosyncratic volatility, analyst disagreement, analyst forecast error, and volatility of earnings and cash flows (detailed definitions of the variables are in Appendix A). I find that all volatility/uncertainty measures monotonically increase (most double in magnitude) as one goes from firms with the lowest to firms with the highest past maximum returns/expected skewness (Panel A1/A2). The link between lottery-likeness and volatility is most likely purely statistical and stems from the fact that a longer right tail implies a higher variance. The evidence in Panel A of Table 2 expands on Table 5 of Bali, Cakici, and Whitelaw (2011), who find that sorts on past maximum return create strong sorts on idiosyncratic volatility. The evidence in Panel A is also consistent with evidence in Lu, Wang, and Wang (2014), who find that large price shocks (e.g., large maximum daily return) result in a sharp increase in disagreement that slowly dissipates over a year.

Panel B first looks at growth option measures: market-to-book (the measure of existing growth options), size (the inverse measure of growth options exercised, as suggested by Berk, Green, and Naik, 1999), the R&D-to-assets ratio (the speed with which growth options are being created), as well as future sales growth and future investment-to-assets ratio (the speed with which growth options will be exercised in the future). I find that lottery-like stocks are significantly smaller, invest more in R&D, and have significantly higher future sales growth and future investments, consistent with Bali, Cakici, and Whitelaw (2011), who find similar evidence for market-to-book and size in maximum return sorts.[4]

I then turn to measures of option-likeness of equity due to the existence of risky debt and limited liability: credit rating and O-score (which proxies for the probability of bankruptcy). Credit rating is coded numerically as AAA=1, AA+=2, etc., and thus a higher numerical credit rating implies distress. I find that lottery-like firms have significantly worse credit ratings (roughly BB- vs. BBB+ for the least lottery-like firms) and a significantly higher probability of bankruptcy. Thus, the option-likeness created by limited liability is a more important consideration for lottery-like firms.

Lastly, I turn to the general convexity measure from Grullon et al. (2012) – the slope on the squared earnings surprise ("SUE flex" in the table) from the regression of earnings announcement returns on the earnings surprise and its square. This convexity measure can capture various kinds of equity option-likeness. Consistent with the rest of Panel B, I find that in Panel B1 (B2) equity convexity more than doubles (increases five-fold) as one goes from the least to the most lottery-like stocks. I conclude that lottery stocks also

[4]The only variable in Panel B that delivers a split message is market-to-book, which is positively related to the past maximum return, but negatively related to expected skewness.

have option-like equity and high firm-specific uncertainty, which would make them hedges against aggregate volatility risk according to my hypothesis.

3.3 Explaining the maximum effect and the skewness effect

In Panel A of Table 3, I examine the alphas and FVIX betas of value-weighted quintile portfolios sorted on maximum daily return in the past month. The alpha rows (CAPM, Fama-French, Carhart) confirm the results of Bali et al. (2011) by revealing that sorting firms on the past maximum return produces 95 bp (72 bp, 54.5 bp) per month differential in value-weighted CAPM (Fama-French, Carhart) alphas.[5] The alpha differential is driven primarily by large and significant negative alphas of lottery-like stocks. When I control for aggregate volatility risk by adding FVIX to either the CAPM or Fama-French or Carhart model, I find that the maximum effect of Bali et al. (2011) is reduced to -2 bp per month or 18 bp or -1 bp per month, respectively. The FVIX betas in the two-factor ICAPM with MKT and FVIX, the four-factor FF4 model (MKT, SMB, HML, and FVIX), and the five-factor Carhart5 model (MKT, SMB, HML, momentum, and FVIX) reveal significant hedging power of lottery-like stocks against aggregate volatility risk, which helps to explain their negative alphas in the CAPM, Fama-French (1993), and Carhart (1997) models.

Panel B displays the alphas and FVIX betas of value-weighted skewness quintile portfolios. In the alpha rows, I find that the skewness effect is at 42 bp (34 bp, 29 bp) per month in CAPM (Fama-French, Carhart) alphas. Similar to the maximum effect, the skewness effect is driven primarily by the negative alphas of firms with the most positive skewness (lottery-like firms). However, once aggregate volatility risk is controlled for, the skewness effect largely disappears. The low-minus-high alpha differential flips the sign

[5] The alpha differential is somewhat smaller than in Bali et al., because Bali et al. do not exclude stocks priced below $5 at the portfolio formation date.

and becomes -31 bp per month (insignificant) in the two-factor ICAPM alphas. In the four factor model (the three Fama-French factors plus FVIX) and in the Carhart model augmented with FVIX, the skewness effect is reduced to 11 bp and 5 bp per month. In the FVIX beta rows, I document the hedging ability of firms with the most positive skewness against aggregate volatility risk (significantly positive FVIX betas) and the exposure of firms with the most negative skewness to such risk. This pattern in FVIX betas is statistically significant and robust to controlling for the Fama-French factors and the momentum factor.

4 Maximum effect, skewness effect, and option-like equity

4.1 Maximum effect, skewness effect, and growth options

The aggregate volatility risk explanation of the maximum effect and skewness effect predicts that firms with lottery-like returns will only be hedges against aggregate volatility risk if they have option-like equity. Hence, I explore two predictions that are new to the literature: that the two lottery effects are stronger for growth firms and that this regularity is explained by the FVIX factor. In Panel A1 of Table 4, I look at returns to the low-minus-high portfolio that buys/shorts firms in the bottom/top 30% in terms of maximum past returns. This portfolio is formed separately within each market-to-book group (top 30%, middle 40%, bottom 30%). Panel A1 reports the CAPM and ICAPM alphas, as well as FVIX betas, of such arbitrage portfolios for each market-to-book group.[6]

[6] Due to the negative relation between leverage and market-to-book and the fact that the aggregate volatility risk explanation of the maximum/skewness effects implies that they are also stronger for distressed firms (see the next subsection), I make the market-to-book sorts conditional on leverage. I first sort on leverage, then on market-to-book within each leverage group, and then on past maximum return or expected skewness in each leverage/market-to-book group. All results are robust to not pre-sorting

In the alpha rows of Panel A1, I report the CAPM/Fama-French/Carhart alphas and find that the maximum effect is significantly stronger (by 52.2-64.5 bp per month, depending on the benchmark model) for growth firms than for value firms. The significant maximum effect is confined to the top two market-to-book groups (only the very top group in the Carhart alphas). This pattern is consistent with the aggregate volatility risk explanation of the maximum effect.[7]

Controlling for the FVIX factor reduces the relation between the maximum effect and market-to-book by at least one-half, just as my explanation of the maximum effect predicts. Controlling for FVIX also makes the maximum effect in the ICAPM/FF4/Carhart5 alphas insignificant even for growth firms (for which it is at 0.59%-1.01% per month in the CAPM/Fama-French/Carhart alphas). Also consistent with my hypothesis, the negative FVIX beta of the low-minus-high maximum portfolio is small in the value subsample and significantly more negative in the growth subsample, revealing that the stronger maximum effect for growth firms comes at the cost of suffering worse losses in response to unexpected increases in aggregate volatility.

In Panel A2, I repeat the analysis for the skewness effect by looking at the alphas and FVIX betas of a low-minus-high arbitrage portfolio that buys/shorts firms with the most negative/positive skewness formed separately in each market-to-book group. In the alpha rows of Panel A2, I find that the skewness effect indeed exists only for growth firms, where it is at 39.4-57.8 bp per month depending on the benchmark model. I also find that the

firms on leverage.

[7]In untabulated results, I look at average maximum return/expected skewness across the double sorts and find that the spread in these variables between top and bottom group is similar in all market-to-book group, thus confirming that the relation between the lottery effects and market-to-book Panel A of Table 4 attempts to discover is unlikely to be mechanical. I also perform the same exercise with the same conclusion for double sorts on O-score and maximum return/expected skewness in the next subsection.

skewness effect is by 47.1-62.5 bp per month stronger for growth firms than for value firms.

The skewness effect for growth firms is reduced to -3.3 bp (13.7 bp) per month after I add FVIX to the CAPM (Carhart model). Adding FVIX to the Fama-French model is less successful and leaves the skewness effect for growth firms at 37 bp per month (*t*-statistic 1.62), but this is still 40% below the Fama-French alpha. Similarly, the difference in the skewness effect between value and growth firms declines to 19.2-28.5 bp per month (statistically insignificant) depending on what model I augment with FVIX.

Panel A2 also reveals that the low-minus-high skewness portfolio indeed demonstrates more negative FVIX betas in the growth subsample. In untabulated results, I find that the more negative FVIX betas are caused by higher hedging ability of positive skewness (lottery-like) firms in the growth subsample, and shorting those firms makes the FVIX beta of the low-minus-high portfolio negative.

4.2 Maximum effect, skewness effect, and equity as a call option on the assets

Another channel through which the aggregate volatility risk explanation of the maximum and skewness effects can work is the option-likeness of equity caused by the existence of risky debt and limited liability. If the firm is close to bankruptcy, its equity is essentially a call option on the assets with the strike price equal to the amount of debt. If idiosyncratic volatility of the assets and aggregate volatility both increase, the value of the option (the equity) will increase and its beta will decrease, holding all else fixed. Thus, the equity will become a hedge against aggregate volatility risk, and more so if the idiosyncratic volatility of the assets is high, as is the case for lottery-like firms (see Table 2), and probability of bankruptcy is high.[8] In the empirical tests in Panel B of Table 4 I use Ohlson's (1980)

[8]For firms with low probability of bankruptcy, the option-likeness of equity is not an important concern

O-score as a measure of bankruptcy probability.[9]

Therefore, I make two new predictions: the maximum effect and skewness effect will be stronger for the firms with high O-score and this regularity will be explained by aggregate volatility risk. I test these hypotheses in Panel B of Table 4, in which Panel B1 (B2) looks at the relation between the maximum (skewness) effect and O-score. As in Panel A, I form low-minus-high portfolios that buy/short firms in the bottom/top 30% in terms of past maximum returns or expected skewness, separately within each O-score group (best 30%, middle 40%, and worst 30%).[10]

In the alpha rows, which report the CAPM/Fama-French/Carhart alphas, both the maximum and skewness effects are usually small and insignificant in the low O-score group, marginally significant in the group with intermediate O-score, and large (up to roughly 1% per month) in the high O-score group. The difference in the maximum/skewness effect between firms with high and low O-score is 59-69 bp/46-71 bp per month. When I look at the alphas controlling for FVIX, I find no significant evidence that the maximum effect or skewness effect are related to O-score, which suggests that aggregate volatility risk can be an explanation the relation between lottery effects and O-score. Likewise, adding FVIX to any of the baseline models reduces the lottery effects for high O-score firms (for which it is the strongest) to within one standard error from zero.

The FVIX betas of the low-minus-high portfolio that shorts/buys lottery/non-lottery

as this option is too deeply in the money.

[9]I refrain from using leverage instead of O-score due to the already mentioned strong negative relation between leverage and market-to-book, which is in part mechanical (market cap is in the numerator of one and in the denominator of the other), and the fact that my explanation of the maximum/skewness effects predicts them to be stronger for growth firms and distressed firms.

[10]Similar to Panel A, I make the sorts on O-score conditional on market-to-book by first sorting on market-to-book, then on O-score, and then on past maximum return or expected skewness. The results in Panel B are robust to not conditioning the O-score sorts on market-to-book.

stocks become more monotonically negative as one goes from the low O-score group to high O-score group. This pattern in FVIX betas suggests that the stronger lottery effects for high O-score firms can arise because in this subsample, the low-minus-high portfolio tends to suffer worse losses during periods of increasing aggregate volatility due to shorting option-like equity with high firm-specific volatility/uncertainty, since such equity provides the best hedge against aggregate volatility risk.

5 Minimum effect: A discriminating test

In this section, I present a potential discriminating test between the lottery preference explanation and the aggregate volatility risk explanation. The discriminating test does not rely on the FVIX factor. If investors have a taste for lottery-like stocks (or positive skewness in general) or tend to overestimate small probabilities, they should also demonstrate an aversion to stocks with long left tails, which are exactly the opposite of lotteries. That is, if I sort firms on the minimum daily returns in the past month, I should observe the minimum effect that is the mirror image of the maximum effect: firms with the most negative past minimum returns should have the highest expected returns.

According to my hypothesis, though, the reason why lottery-like stocks earn low future returns is that they are volatile and therefore load positively on FVIX. If volatility, not lottery-likeness, is the main variable, then stocks with large minimum returns should earn low returns as well, because they are just as volatile as stocks with high maximum returns.

Since stocks with a long right tail are also likely to have a long left tail, the maximum and minimum effects are likely to overlap. On the one hand, this is the point: "lottery-like" stocks are also likely to be "disaster" stocks (and in fact, both are just volatile stocks). On the other hand, one may be concerned that simple sorts on past minimum returns will re-discover the maximum effect. Hence, instead of looking at raw minimum returns, I look at minimum returns orthogonalized to maximum returns (RMin). In each month, I perform a cross-sectional regression of minimum daily return in that month on maximum daily return in the same month and denote the residual as RMin.

Table 5 repeats Table 2 for quintile sorts on RMin and reports median values of firm-specific uncertainty measures and option-likeness measures across the RMin quintiles. For ease of comparison with the maximum effect, the minimum returns are multiplied by -1, so that the high RMin quintile is the quintile with the most negative RMin. Similar to Table 2, Table 5 shows that firms with the most negative RMin ("disaster stocks") are very similar to firms with the most positive maximum returns ("lottery stocks"): they are high uncertainty, option-like firms. All measures of uncertainty and option-likeness (except for future sales growth and future investment) demonstrate sizeable and statistically significant differences between firms with the least and most negative RMin.

Panel C looks at median maximum and minimum returns across RMin sorts. The point of creating RMin is to create two portfolios that would be comparable in terms of past maximum return, but very different in terms of past minimum return, which is achieved in the top and bottom RMin quintiles. The spread in minimum return between those is only 10% smaller than the quintile spread in minimum return from the sorts on minimum return itself (not tabulated), but the spread in maximum return is very small.

This conclusion is supported by the bottom two rows of Panel C, which tabulates the fraction of firms in top maximum/minimum decile in each RMin quintile. It turns out that extreme RMin quintiles are very similar in terms of fraction of firms from the top maximum decile (roughly 16% in each one), but are very dissimilar in the faction of firms from the top minimum decile (46.8% vs. 0.6%), exactly what RMin is aiming at.[11]

Panel A in Table 6 looks at alphas and FVIX betas of RMin quintiles. In the CAPM/Fama-French/Carhart alpha rows, the minimum effect is just as strong as the maximum effect. The differential in CAPM (Fama-French, Carhart) alphas between firms with the most and least negative minimum returns is 70.5 bp (61.5 bp, 43.6 bp) per month, all statistically significant. Also, the minimum effect is driven exclusively by the large negative alphas of the "disaster stocks." Hence, it seems that investors not only go for lotteries, but also court disaster, overpaying for stocks with the highest chance of a huge loss. This is true even after controlling for maximum return, i.e., investors do not end up pursuing stocks with a long left tail as a by-product of their effort to hold lottery stocks. Such behavior is inconsistent with the lottery/skewness preference, but consistent with my theory that argues that it is volatility, not lottery-likeness, that matters.[12]

Panel A of Table 6 shows that the FVIX factor largely explains the minimum effect, bringing it to 2 bp per month in the ICAPM with the market factor and FVIX and to 10 bp per month in Carhart5. Similarly, the large negative CAPM/Carhart alphas of the "disaster stocks" are reduced from -63 and -43 bp per month to -19.2 and -18.7 bp per month after controlling for FVIX.[13] I also find that FVIX betas increase significantly

[11] One can also notice the U-shape in maximum return in RMin quintiles, which is rather common for orthogonalized measures. Orthogonalization sets the correlation between the two variables (RMin and MAX in my case) to zero, and one way to do that is to form a U-shape so that for some values of RMin it is positively related to MAX, for some values it is negatively related to MAX, and the average correlation between MAX and RMin is zero.

[12] It is also interesting that the minimum effect is similar in size if I do not orthogonalize minimum return to maximum return, which seems to suggest that there is not as much overlap between the maximum and minimum effects as one would think looking at the correlation between maximum and minimum returns.

[13] Adding FVIX to the Fama-French model produces more modest reduction in the minimum effect and the alphas of "disaster stocks", which are reduced by about one-half, but remain (marginally) significant. In untabulated results, I find that this is driven by small stocks, because replacing CRSP breakpoints for RMin sorts by NYSE breakpoints preserves all results in Panel A of Table 6, but reduces the minimum

and monotonically across the minimum return quintiles and reach significantly positive values for the "disaster stocks," indicating that such stocks are a hedge against aggregate volatility risk, as predicted by my hypothesis.[14]

Prior studies of the maximum and minimum effects (Bali et al., 2011; Annaert et al., 2013) use cross-sectional regressions instead of portfolio sorts and do not find a significant minimum effect. The first two rows of Panel A, however, suggest that the relation between past minimum returns and expected returns is highly nonlinear: it has a weak hump-shape in the bottom four quintiles followed by a sharp drop in the fifth quintile.[15] Thus, in the cross-sectional regressions, that relation, which is assumed to be linear, is severely misspecified. In untabulated results, I find that, first, the minimum effect is strong and significant if I use the top quintile dummy instead of the continuous variable (using the dummy assumes the relation between past minimum returns and future returns that is very close to the "flat, then down" pattern in portfolio sorts) and, second, that even with the continuous variable the minimum effect is strong and significant if I exclude as little as 20% of firms with the smallest (by absolute magnitude) minimum return.

In Panel B of Table 6, I repeat Table 4 by looking at the minimum effect across market-to-book and O-score groups.[16] The results are very similar to Table 4: the minimum effect is absent for value and neutral firms and is stronger by 50 bp per month for growth firms, however, controlling for FVIX largely explains this pattern. FVIX betas also reveal that buying firms with the least and shorting firms with the most negative RMin exposes the

effect in the four-factor model (the three Fama-French factors and FVIX) to 6.7 bp per month, and the four-factor alpha of "disaster stocks" to -17.3 bp per month.

[14]In untabulated results, I find that the results in Panel A of Table 6 are robust to using equal-weighted returns and/or NYSE breakpoints, as well as to not orthogonalizing minimum return to maximum return.

[15]Sorts on raw minimum returns rather than RMin create a very similar pattern in the alphas with a somewhat weaker U-shape.

[16]Similar to Table 4, the sorts on market-to-book are conditional on leverage, and the sorts on O-score are conditional on market-to-book. The results are robust to not performing the conditioning.

investor to greater aggregate volatility risk if performed in the growth subsample. Likewise, the minimum effect is zero for healthy firms with low O-score and it is stronger by at least 60 bp per month for option-like distressed firms and controlling for FVIX largely eliminates this pattern as well.

In untabulated results, I also attempt to make sure that the minimum effect does not pick up the maximum effect in a different fashion. Since the majority of the maximum effect is coming from the top maximum quintile, I drop all firms in the top maximum quintile from the sample prior to portfolio formation and sort the remaining firms on past minimum return (if the firm makes into the top maximum quintile during the performance measurement month, it stays in the sample). This way, no firms from the top maximum quintile will be in the top minimum quintile; if minimum return is just a proxy for maximum return, then the minimum effect in this truncated sample will be quite weak. However, in untabulated results, I find that the minimum effect, as well as its relation to equity option-likeness and its aggregate volatility risk explanation, are almost as strong in the truncated sample as in the full sample. That suggests that the minimum effect is an independent phenomenon and not the maximum effect in disguise.

The existence of the minimum effect and the evidence that it behaves the same way as the maximum effect (disappears after controlling for FVIX, becomes stronger for option-like firms) suggests that the low returns to lottery-like stocks are due to their higher idiosyncratic volatility and hence lower aggregate volatility risk, not to a preference for lotteries. In a world with a preference for lotteries, “disaster stocks” should have higher, not lower returns, whereas under the volatility risk explanation, maximum and minimum returns should affect future returns in the same way, since both essentially substitute for individual stock volatility/uncertainty.

6 Characteristics vs. covariances

The analysis thus far suggests that lottery characteristics are correlated with FVIX betas, and only their common part is priced. On the one hand, the risk-based explanation I present makes the prediction that lottery-likeness characteristics are related to FVIX betas, and the mispricing explanations make no such prediction. Also, the relation of the lottery effects to market-to-book and O-score and the ability of FVIX to explain this relation is another piece of indirect evidence that volatility risk can explain the lottery effects. On the other hand, it is still possible that the common variation in FVIX betas and lottery characteristics is mispricing-driven.

As Daniel and Titman (1997) argue, the ultimate test of a mispricing vs. risk-based hypothesis is to show that the variation in the characteristic that is unrelated to the covariance is not priced, while the variation in the covariance unrelated to the characteristic is priced. If this is the case, then the risk-based hypothesis is likely to be true, and the covariance explains why the characteristic is priced. If the reverse is true, then the mispricing hypothesis is true and the characteristic explains why the covariance is priced. A mixed result would suggest that the risk-based and mispricing hypotheses co-exist. There are two ways to perform the test described above. One is to perform a horse race between volatility risk and lottery effects in cross-sectional regressions. Another is to perform portfolio sorts on FVIX beta while controlling for lottery-likeness and vice versa. Subsections 6.1 and 6.2 follow the first approach, leaving the other one for Subsection 6.3.

6.1 Lottery effects in portfolio-level regressions

Panels A and B of Table 7 present portfolio-level cross-sectional regressions of future stock returns on the lottery-likeness characteristics, FVIX betas, and the standard control variables: market beta, log size, market-to-book, momentum (i.e., cumulative returns between months t-12 and t-2), and short-term reversal (return in month t-1). Panel A uses the standard five-by-five sorts on size and market-to-book as the test assets. Panel B uses the five-by-five sorts on market-to-book and the lottery-likeness measures as denoted in the columns heading. All left-hand side variables (e.g., maximum/minumum return, market beta, and FVIX beta) are measured for individual firms, winsorized at 1% within each month, and then averaged across all firms in the portfolio to arrive at the portfolio value of the explanatory variable.[17]

The first column of Panel A regresses future returns on FVIX betas and the standard controls. The FVIX beta comes out marginally significant with the risk premium of -85.7 bp per month, which is close to the quintile spread from the sorts on FVIX beta (see Panel A of Table 9 below). Columns two, four, and six confirm that the lottery effects are visible in the cross-sectional regressions and both the past maximum/minimum return and expected skewness are negatively related to expected returns.[18]

Columns three, five, and seven use both the FVIX beta and one of the lottery-likeness variables, thus performing the required horse race. The evidence in columns three and five is consistent with my hypothesis that variation in FVIX betas that is unrelated to variation in lottery-likeness is priced, and variation in lottery-likeness that is unrelated to variation in FVIX betas is not priced.[19] In the presence of FVIX beta, past maximum/minimum return slope is reduced by about one-half and becomes insignificant, while

[17] Since extreme returns tend to diversify away at the portfolio level, it is important that Panels A and B of Table 7 define the maximum/minimum return (and expected skewness) at the portfolio level as the average maximum/minimum return (or average skewness) of all stocks in the portfolio and not as the maximum/minumum portfolio return in the past month (or portfolio skewness).

[18] Numerically, the minimum effect is as strong as the maximum effect, but the estimate is more noisy and only significant at 10% level.

[19] However, the confidence intervals for the slopes on lottery variables are large and include economically significant values of the lottery effect even after controlling for FVIX beta.

the FVIX beta slope does not change much in terms of its magnitude/significance when past maximum/minimum return is controlled for. In column seven, FVIX beta and expected skewness both decline by about 30% and lose significance, confirming the strong relation between them, but making me unable to call the winner.

Panel B changes the test assets to five-by-five sorts on market-to-book and lottery-likeness. As Lewellen, Nagel, and Shanken (2010) show, many portfolio sets have a strong factor structure, which can obscure the results, and thus repeating the asset-pricing tests with several portfolio sets as test assets is advisable. In the first three columns, I use five-by-five sorts on market-to-book and past maximum return. The first column shows that the slope on FVIX beta stays the same as in Panel A and even becomes more significant, which confirms the robustness of FVIX beta pricing. In the second column, past maximum return is surprisingly weaker than in Panel B (one would expect that maximum return will be better in explaining returns to maximum sorts than in explaining returns to any other sorts), but still marginally significant at the 5% level. Using FVIX beta and past maximum return in column three makes the slope on FVIX beta and its significance increase slightly, and the slope on past maximum return decreases by about 60% and becomes insignificant.

In the next three columns, I use the five-by-five sorts on market-to-book and past minimum returns. The idea is to try another set of base assets and to make the minimum effect more challenging to explain by trying a portfolio set, the returns to which should be related to minimum return by construction. The minimum effect comes out more significant than in Panel A, though the slope is numerically somewhat smaller, and FVIX beta still has about the same slope as in Panel A and can explain at least one-half of the minimum effect (rendering the other part insignificant). The last three columns in Panel B replace the test assets with five-by-five sorts on market-to-book and expected skewness and perform the horse race between FVIX beta and expected skewness. In contrast to Panel A, FVIX beta emerges as a winner, because in the regression that has both FVIX beta and expected skewness (column nine) FVIX beta slope stays large and significant, and expected skewness slope declines by 40% and becomes insignificant.[20]

6.2 Lottery effects in firm-level regressions

Panel A of Table 8 repeats the regressions in Table 7 at the firm level. The benefit of that is a richer cross-section that captures the information potentially lost at the portfolio level and makes the standard errors smaller. The downside is that the firm-level regressions are likely to suffer from errors-in-variables, which will make slopes on FVIX beta and potentially on lottery-likeness measures biased towards zero. (Portfolio-level regressions in Table 7 handle errors-in-variables by averaging them out within a portfolio. Thus, the choice between Tables 7 and 8 is essentially the choice between robust and efficient estimation).

Comparing the results in Panel A of Table 8 to Table 7, I find that the slopes on FVIX beta (lottery-likeness variables) are roughly three (two) times smaller in Panel A of Table 8 than in Table 7. Both FVIX beta and lottery likeness variables are still significant due to the equally smaller standard errors. Contrary to all previously used methods (including portfolio sorts in Tables 3 and 6 and the upcoming conditional sorts in Table 10), Panel A estimates the overlap between FVIX beta and the lottery-likeness variables to be small. If both are used in one regression (see columns three, five, and seven), the slope on FVIX beta barely changes, while the slope on the lottery likeness variable decreases by 10-15%.

One possible explanation of why the overlap between FVIX beta and the lottery likeness

[20]The results in Panel B would be qualitatively similar if I stuck with one set of test assets (e.g., five-by-five sorts on market-to-book and past maximum returns) for all columns in Panel B.

variables is roughly three times smaller in the firm-level regressions is errors-in-variables, which presumably cause firm-level regressions to underestimate the risk premium (slope) of FVIX by a factor of three (compare again Panel A of Table 8 and Table 7), and then it is not surprising that the ability of FVIX beta to explain the lottery effect is underestimated by a factor of three as well.[21]

Another potential explanation of the small overlap between FVIX beta and the lottery likeness variables in firm-level regressions is that the regressions assume the relation between those variables and expected returns is linear, while portfolio sorts in Tables 3, 6, and 9 show that a weak hump-shape in the bottom four quintiles is followed by a sharp drop in the top quintile, and the drop creates the majority of the lottery effects and FVIX beta pricing.

Thus, the linear models in Table 7 and Panel A of Table 8 can potentially be misspecified. This misspecification would be less of an issue in Table 7, because the cross-section of 25 portfolios is not large enough for the non-linearities to manifest themselves, but could impact the results in Panel A of Table 8. Therefore, Panel B of Table 8 replaces lottery-likeness measures and FVIX betas by dummy variables that are equal to one if the respective variable is in the top cross-sectional quintile in the previous month and zero otherwise. All other control variables remain untransformed.

The main difference between Panels A and B is that in Panel B the horse race between FVIX beta and lottery-likeness ends with aggregate volatility risk subsuming more than 100% of the lottery effects (the slope on the top FVIX beta quintile dummy also declines by roughly 50% controlling for lottery-likeness). For example, in column three the slope

[21] Another manifestation of the errors-in-variables problem is in cross-sectional correlations between FVIX beta and the lottery likeness variables, which are around 0.2 at the firm level and around 0.6 at the portfolio level (the noise in the variables does not affect their covariance, but makes the standard deviations it is divided by larger).

on the top FVIX beta quintile dummy (HiFVIX) implies that firms that are in the top FVIX quintile, but not in the top maximum quintile earn -15.8 bp per month on the risk-adjusted basis (statistically significant), and the slope on the similar HiMAX dummy says that firms that are in the top maximum quintile, but not in the top FVIX beta quintile earn a positive 18.3 bp per month abnormal return (marginally significant).[22]

Of course, the step-wise relation between FVIX beta/lottery likeness and expected return assumed in Panel B is also simplistic (though arguably closer to reality than the linear relation), and the models in Panel B can still be misspecified and can be hiding the fact that FVIX has some trouble with explaining the apparent hump-shape in the portfolio sorts on lottery-likeness. But even if that is true, the lack of overlap between FVIX beta and lottery-likeness measures in Panel A still does not imply the inability of aggregate volatility risk to explain the negative alphas of lottery-like stocks, but rather comes from the combination of the linear model misspecification and errors in variables.[23]

In untabulated results, I also follow the approach in Brennan, Chordia, and Subrahmanyam (1998) in performing firm-level cross-sectional regressions with risk-adjusted returns on the left-hand side. As Brennan et al. point out, this approach eliminates the errors-in-variables problem for risk loadings, which are always estimated and not observed.[24] Across all three effects, a very similar pattern emerges: they are all strong in raw returns and in risk-adjusted returns, if the risk-adjustment includes the standard asset-pricing factors (market, SMB, HML), but largely disappear if the risk-adjustment

[22]If one interprets the slopes on the top quintile dummies in columns one, two, four, and six as (roughly) the alphas of the top quintile, one can see that the errors-in-variables problem is still present in Panel B, since portfolio sorts usually yield almost twice larger estimates of the said alpha.

[23]The lack of overlap between FVIX beta and lottery-likeness measures in Panel A can come from the fact that FVIX beta does not capture the full complexity (e.g., the hump-shape) of relation between lottery likeness and expected returns, but, according to portfolio sorts, the hump-shape does not usually create significant alphas in the middle quintiles and therefore is not a major anomaly.

[24]Brennan et al. regressions handle the errors-in-variables problem only for the betas, thus allegedly putting other variables (e.g., lottery likeness), which can also be measured with error, at a disadvantage.

includes FVIX. Controlling for FVIX on the left-hand side generally makes all three effects two to three times weaker than they were prior to controlling for FVIX and leaves all of them statistically insignificant. The firm-level regressions with risk-adjusted returns as the dependent variable confirm the robustness of results in Table 7 and support the errors-in-variables explanation of the difference between Table 7 and Panel A of Table 8.

6.3 Lottery-likeness vs. FVIX beta pricing in portfolio sorts

Tables 9 and 10 perform sorts on FVIX betas while controlling for lottery characteristics and sorts on a lottery characteristic while controlling for FVIX beta, respectively. To make sure that one variable in the sorts varies while the other does not, I orthogonalize the variables by performing a cross-sectional regression of one variable onto another in each portfolio formation month and then use the residual as the sorting variable. For example, Table 9 presents the results of the sorts on untransformed historical FVIX beta in Panel A, and then in Panel C uses instead as the sorting variable the residual from the cross-sectional regression of historical FVIX beta on the maximum return in the same (portfolio formation) month. In Panel B (D), the sorting variable is a similar residual from the regression of FVIX beta on expected skewness (minimum return).[25]

Panel A of Table 9 shows that sorting firms on historical FVIX betas results in a monthly CAPM/Fama-French/Carhart alpha spread of 68/54/41 bp per month. The spread is primarily driven by the negative alphas of the quintile with the most positive FVIX betas (the firms in this quintile are the best hedges against aggregate volatility

[25]The orthogonalization approach is superior to conditional sorts, because the residual is unrelated to the variable I want to hold constant by construction, while conditional sorts (e.g., first on maximum daily return, then on FVIX beta) do not guarantee that the first characteristic will be exactly the same in all groups based on the second variable. While conditional sorts will produce a smaller spread in the conditioning characteristic than unconditional sorts, if the two variables are related (as FVIX betas and lottery-likeness measures should be under my hypothesis), sorting on the second variable (in each group based on the first variable) will still produce a non-negligible spread in the first variable.

risk). Panels B, C and D use the FVIX betas orthogonalized to past maximum return, expected skewness, or past minimum return and show that this orthogonalization does not materially affect the alpha spread between top and bottom FVIX beta quintiles, making it smaller by roughly 5-16 bp per month and leaving it statistically significant. The alphas of the top FVIX beta quintile are similarly unaffected.[26]

Table 9 shows that the variation in FVIX betas that is unrelated to lottery characteristics is strongly priced. Moreover, it appears that controlling for lottery characteristics explains only a small part of FVIX beta pricing, suggesting that FVIX betas are priced for reasons almost completely different from their correlation with lottery-likeness.

The mispricing explanation of the lottery effects does not say though that the lottery effects should explain why aggregate volatility risk is priced. While Table 9 shows that the pricing of FVIX betas comes from sources other than their relation with lottery characteristics, thus making it more likely that the ability of the FVIX factor to explain the lottery effects is not mechanical, but rather reflects a genuine ability of aggregate volatility risk (a broader phenomenon) to explain the lottery effects (one of its manifestations), Table 9 does not formally address the mispricing explanation of the lottery effects.

The horse race with the mispricing explanation happens in Table 10, which sorts firms on lottery characteristics orthogonalized to FVIX. In each month, I regress the lottery characteristics on firm-level historical FVIX beta (from the two-factor ICAPM with market and FVIX) and use the residual to perform the sorts in Table 10. The results in Table 10 should be compared to the CAPM/Fama-French/Carhart alphas in Table 3 and in Panel A of Table 6. Such comparison finds that the effects decline by 60% to 115% and

[26]A possible exception is Panel B, in which orthogonalizing FVIX betas to expected skewness reduces the alphas of the top FVIX beta quintile by roughly 20 bp per month, but still leaves them economically large (-26 to -39 bp per month) and statistically (marginally) significant.

usually become insignificant if the lottery characteristics are orthogonalized to FVIX beta. The alphas of the top lottery-likeness quintile usually witness an even larger decline after orthogonalization.[27] Thus, Table 10 shows that the variation in the lottery characteristics that is unrelated to FVIX betas, is largely not priced, and in almost all cases I cannot reject the hypothesis that lottery-likeness is unrelated to expected returns once aggregate volatility risk is controlled for.[28]

7 Robustness checks

7.1 Alternative 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. The C-GARCH model assumes that market volatility has two components, the short-run component – the shocks to which quickly die out – and the long-run component – with extremely persistent shocks. Chen and Petkova (2012) follow a different route and argue that the true state variable is average total volatility, not market volatility. Chen and Petkova also show that the average volatility factor helps to explain the idiosyncratic volatility discount of Ang et al. (2006), which is a close relative of the maximum and skewness effects.

In untabulated results, I find that the short-run and long-run volatility factors help

[27] In the sorts on past maximum return orthogonalized to FVIX beta (Panel D), the top maximum quintile continues to have significant CAPM/Fama-French alphas, and its difference with the respective alphas of the bottom maximum quintile is still marginally significant, but the alpha decline due to the FVIX control is still more than 50% for the top quintile alphas and more than 60% for the top-bottom alpha differential.

[28] However, the confidence intervals for the quintile spreads in alphas in the sorts on lottery likeness orthogonalized to FVIX beta are quite large and do not exclude the possibility that the true value of the lottery effects controlling for volatility risk is 30-50 bp per month.

explain about 25–50 bp per month of the lottery effects, but the lottery effects remain economically large and statistically significant unless I add FVIX to the Adrian and Rosenberg factors. I also observe that only the short-run volatility factor helps to explain the lottery effects and also overlaps significantly with FVIX, shedding light on the nature of (the priced part of) FVIX - it captures relatively short-run changes in physical volatility and not risk aversion. Another implication of the overlap between FVIX and short-run volatility factor is that the latter can serve as a replacement for FVIX pre-1986, when the VIX index is not available.

As for the average volatility factor of Chen and Petkova (2012), I find, somewhat unexpectedly, that it has virtually no ability to explain the lottery effects and does not overlap with FVIX. The cause of the difference between my results and Chen and Petkova (2012) is the absence in my analysis of the innovations to average correlation (between all stocks in the sample). Chen and Petkova use average correlation to create the base assets for the factor-mimicking portfolio that tracks innovations to average volatility despite their finding that average correlation is not priced. Removing the seemingly irrelevant average correlation from the analysis makes the risk premium of the average volatility factor four times smaller and destroys its ability to explain the idiosyncratic discount, the focus of Chen and Petkova (2012)[29]

I have also checked that my results are robust to alternative methods of forming the FVIX factor (results of the robustness tests are available upon request). I found that the results in Tables 3-6, as well as the results in Table 1, do not materially change if I use ten industry portfolios from Fama and French (1997) as the base assets for forming FVIX, or if I exclude from the base assets firms that are in the top quintile in terms of past maximum

[29]Herskovic et al. (2016) use a similar average volatility factor and also find that it is priced, but cannot explain the idiosyncratic volatility discount.

return (expected skewness, idiosyncratic volatility). The latter result suggests that the explanatory power of FVIX is not mechanical, which is further confirmed by another untabulated test: I find while controlling for FVIX can explain the return differential between firms with high and low past maximum return (expected skewness), the return differential cannot explain the alpha of FVIX if used as a factor.

7.2 Alternative portfolio sorts

In untabulated results, I test the robustness of my explanation of the maximum effect to using alternative measures of past maximum returns that average the top five daily returns in a month (Max5 measure in Bali et al., 2011) or average the top two daily returns in a month (Max2 measure). Bali et al. find that sorting firms on Max5 produces a significantly stronger maximum effect, the finding that I confirm in my sample period (in the CAPM alphas, the Max5 effect is 30% stronger than the maximum effect in Table 3, in the Carhart alphas, the Max5 effect is 53% stronger).

The strong negative relation between the past maximum return and aggregate volatility risk is preserved when I use Max5 measure. Moreover, adding FVIX to the CAPM (Carhart model) reduces the low-minus-high alpha differential to 12 bp (19 bp) per month and renders it statistically insignificant. The large and negative alphas of the top quintile witness a similar decline from -93 bp (-68 bp) per month to -11 bp (-22 bp) per month.

Also in untabulated results, I test the robustness of the evidence in Table 3 to using equal-weighted returns, using NYSE breakpoints, and using decile sorts instead of quintile sorts. I find that the relation of aggregate volatility risk exposure and lottery-likeness, as well as the ability of FVIX to explain the maximum and skewness effects is preserved under all these scenarios. In particular, controlling for FVIX renders the low-minus-high decile spread in alphas insignificant in both maximum sorts and expected skewness sorts, despite the fact that both effects are 24% to 48% stronger in the decile sorts. The only problem FVIX has in explaining the maximum and skewness effect arises in equal-weighted quintile sorts, in which the absolute reduction of the low-minus-high portfolio alpha is similar to what I observe in Table 3, but the remaining part of the equal-weighted low-minus-high alpha differential sometimes remains statistically significant. Yet, the strong positive relation between FVIX beta and past maximum return (or expected skewness) is preserved in equal-weighted returns.

I also repeat the double sorts in Table 4 using equal-weighted returns instead of value-weighted ones. The results in Table 4 do not seem to depend on the change in the weighting scheme. In equal-weighted returns, the difference in the maximum/skewness effect between value and growth (distressed and healthy) firms is similar in magnitude and statistically significant. The same is true about the ability of FVIX to explain the said difference and the difference in FVIX betas of the low-minus-high portfolio formed in the value and growth (distressed and healthy) subsamples.

8 Conclusion

The paper argues that one reason why lottery-like stocks (stocks with high positive skewness or large maximum daily return in the previous month) earn low expected returns is that they are a hedge against increases in aggregate volatility. I find that lottery-like stocks have positive FVIX betas and therefore outperform the CAPM prediction when VIX unexpectedly goes up (FVIX is an aggregate volatility risk factor positively correlated with VIX changes). I also find that controlling for FVIX reduces by 50-100% two anomalies usually attributed to the overpricing of lottery-like stocks: the maximum effect of Bali, Cakici, and Whitelaw (2011) and the skewness effect of Boyer, Mitton, and Vorkink (2010).

The intuition behind my explanation of low expected returns to lottery-like stocks is that lottery-like stocks are typically volatile stocks with option-like equity, and such stocks are hedges against aggregate volatility risk, as Barinov (2011, 2013) finds. I find that firms with highly positive skewness or large past maximum return indeed have higher firm-specific volatility/uncertainty, more growth options, and more convex equity values.

I also successfully test several new hypotheses about cross-sectional behavior of the maximum effect and skewness effect. I find that both the maximum effect and skewness effect are stronger for firms with more option-like equity: firms with high market-to-book or high O-score. This evidence is consistent with my hypothesis that lottery-like stocks are a hedge against aggregate volatility risk because their equity is option-like. I also find that the link between the maximum/skewness effects, on one hand, and market-to-book and O-score, on the other, is reduced to insignificance after I control for FVIX, further supporting my main hypothesis that the maximum effect and skewness effect stem from the fact that lottery-like stocks are hedges against aggregate volatility risk.

Another new piece of evidence is the existence of the minimum effect, which behaves very similar to the maximum effect and is largely explained by aggregate volatility risk. The minimum effect refers to the fact that firms with more negative past minimum returns earn lower future returns. Its existence is consistent with my idea that extreme (maximum/minimum) past returns proxy for volatility, but not with the existing explanations of the maximum effect, as stocks with the most negative past minimum returns are the exact opposite of lottery-like stocks and thus, under the mispricing stories, should have positive, not negative alphas.

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Appendix A

The variables are arranged in the alphabetical order according to the abbreviated variable name used in the tables.

AV (average volatility) - following Chen and Petkova (2012), I compute average volatility by summing squared daily returns and the doubled products of today's and yesterday's returns in each firm-month and then averaging this sum for all firms in a month. The innovations to the average volatility are from the vector autoregression (VAR) with market returns, SMB, HML, AV, and average correlation between all stocks in a month.

CVEarn/CVCFO (earnings/cash flows volatility) - coefficient of variation (standard deviation over the average) of quarterly earnings/cash flows measured in the past 12 quarters. Earnings are earnings-per-share (EPS, epspiq over prccq lagged by one quarter). Cash flows are operating income before depreciation (oibdpq) less change in current assets (actq) plus change in current liabilities (lctq) less change in short-term debt (dlcq) plus the change in cash (cheq). The cash flows are scaled by average total assets (atq) in the past two years. All variables are from the Compustat quarterly file.

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

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

ES (expected skewness) - the expected value from

$$\begin{aligned} ISkew_t = \quad & \gamma_0 + \gamma_1 \cdot ISkew_{t-60} + \gamma_2 IVol_{t-60} + \gamma_3 \cdot Mom_{t-60} + \gamma_4 \cdot Turn_{t-60} + \\ & + \gamma_5 \cdot NASD_{t-60} + \gamma_6 \cdot Small_{t-60} + \gamma_7 \cdot Med_{t-60} + \Gamma \cdot IndDum. \end{aligned} \quad \text{(A-1)}$$

The regression is performed in cross-section every month. ISkew is idiosyncratic skewness, computed from daily firm-level residuals (ϵ) of the Fama-French model in the past 60 months. ISkew is scaled by idiosyncratic volatility (IVol), computed the same way in the same period, raised to the power of 3/2:

$$ISkew = \frac{\sum_{t \in D} \epsilon_t^3}{(\sum_{t \in D} \epsilon_t^2)^{3/2}}, \tag{A-2}$$

where D is the set of non-missing daily returns in the past 60 months. IVol on the right-hand side of (A-1) is $IVol = \sum_{t \in D} \epsilon_t^2$. Mom is cumulative monthly return in the past 12 months excluding the most recent one, Turn is average monthly turnover in the past year. NASD is a Nasdaq dummy that equals one if the firm is from Nasdaq (exchcd from CRSP events file is equal to 3), and 0 otherwise. Small is a small firms dummy that equals one if the firm is from the bottom three size deciles, zero otherwise. Med is a medium firms dummy that equals one if the firm is in the fourth to seventh size deciles, zero otherwise. Ind are industry dummies that equal one if the firm belongs to a certain industry, zero otherwise. Industries are the 30 industries from Fama and French (1997).

IG (investment growth) - the change in capital expenditures (capx item from Compustat) over the previous year capital expenditures.

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).

Max (maximum daily return) - maximum daily return (from CRSP) in the previous month.

MB (market-to-book) - equity value (item #25 times item #199) divided by book equity (item #60) plus deferred taxes (item #74), all items from Compustat annual.

Min (minimum daily return) - minimum daily return (from CRSP) in the previous month. In portfolio sorts, the minimum return is multiplied by -1 so that "high minimum return" indicates "very negative minimum return."

Mom (cumulative past return) - cumulative return to the stock between months t-2 and t-12.

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

$$O = -1.32 - 0.407 \cdot \ln TA + 6.03 \cdot \frac{TL}{TA} - 1.43 \cdot \frac{WC}{TA} + 0.076 \cdot \frac{CL}{CA} - 1.72 \cdot I(TL > TA)$$
$$-2.37 \cdot \frac{NI}{TA} - 1.83 \cdot \frac{FFO}{TA} + 0.285 \cdot I(NI < 0 \; \& \; NI_{-1} < 0) - 0.521 \cdot \frac{NI - NI_{-1}}{|NI| + |NI_{-1}|}, \quad \text{(A-3)}$$

where *TA* is the book value of total assets (Compustat item at), *TL* is the book value of total liabilities (lt), *WC* is working capital (wcap), *CL* are current liabilities (lct), *CA* are current assets (act), *NI* is net income (ni), NI_{-1} is the previous year net income, *FFO* are funds from operation (pi plus dp), $I(TL > TA)$ is a dummy variable equal to one if the book value of total liabilities exceeds the book value of total assets, and equal to zero otherwise, $I(NI < 0 \; \& \; NI_{-1} < 0)$ is a dummy variable equal to one if the net income was negative in the two most recent years, and equal to zero otherwise. Expected probability of bankruptcy in the next two years, Pr, can be obtained as the logistic transformation of O-score: $Pr = e^O/(1 + e^O)$.

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

RD/TA (R&D-to-assets) - research-and-development expenditures (xrd item from Compustat) divided by total assets (at item from Compustat) in the previous year.

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.

Rev (short-term reversal) - stock return in month *t*-1.

RMIN (residual minimum return) - the residual from the cross-sectional regression

$$Min_i = \gamma_0 + \gamma_1 \cdot Max_i + \epsilon_i, \quad RMin_i = \epsilon_i \quad \text{(A-4)}$$

The regression is performed separately for each month, Min_i and Max_i are minimum and maximum daily returns to firm i in each month, respectively.

RSI (residual short interest) – outstanding shorts reported by NYSE and Nasdaq divided by the number of shares outstanding. The data are monthly and reported on the 15th calendar day of each month.

SG (sales growth) - the change in sales (sale item from Compustat) in percentage of last year's sales: $SG_t = \dfrac{Sales_t - Sales_{t-1}}{Sales_{t-1}}$.

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

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

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

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

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:

$$Ret_t^{CRSP} = \gamma_0 + \gamma_1 \cdot Ret_{t-1}^{CRSP} + \epsilon_t, \quad \sigma_t^2 = c_0 + c_1\sigma_{t-1}^2 + c_2\epsilon_{t-1}^2 + c_3 \cdot I(\epsilon_{t-1} < 0). \tag{A-6}$$

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

Turn (turnover) - trading volume divided by shares outstanding (both from CRSP monthly data). The monthly turnover is then averaged in each calendar year with at least five valid observations. To make comparisons across exchanges more meaningful, I adjust Nasdaq volume for the double-counting following Gao and Ritter (2010): Nasdaq volume is divided by 2.0 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002–2003, and is unchanged after that. A firm is classified as a Nasdaq firm if its CRSP events file listing indicator (exchcd) is equal to 3.

Table 1
FVIX factor as an ICAPM factor

Panel A reports the correlations between FVIX and VIX and its change on the left side, and the alphas and Fama-French/Carhart betas of the FVIX factor on the right side. The FVIX factor is the fitted value less the constant from the regression of daily changes in the VIX index on the daily excess returns to the volatility sensitivity quintiles (please refer to Section 2 for more details). The daily returns of the FVIX factor are then cumulated to the monthly level. Panel B presents the slopes from regressions of business cycle variables (the NBER recession dummy, the VIX index, the TARCH(1,1) forecast of market volatility, and the realized volatility, which is the sum of squared daily returns) on the FVIX factor returns. The regression with the NBER dummy is probit regression. The numbers in the first row are the number of months by which I lag the FVIX factor returns in each column. The slopes (with the exception of the probit regression) indicate the change in the business cycle variables (in percentage points) in response to a 1% return to the FVIX factor. Detailed definitions of all variables are in Appendix A. The *t*-statistics use Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015.

Panel A: FVIX as a factor-mimicking portfolio

	Correlations				FVIX Factor			
	FVIX	ΔVIX	VIX		Raw	CAPM	FF	Carhart
FVIX	1	0.715	0.145	α	-1.308	-0.455	-0.436	-0.442
t-stat.		*88.7*	*12.76*	*t*-stat.	*-4.27*	*-4.50*	*-3.81*	*-3.75*
ΔVIX	0.715	1	0.129	β_{MKT}		-1.341	-1.376	-1.375
t-stat.	*88.7*		*11.29*	*t*-stat.		*-37.2*	*-34.2*	*-33.2*
VIX	0.145	0.129	1	β_{SMB}			0.171	0.171
t-stat.	*12.76*	*11.29*		*t*-stat.			*5.48*	*5.64*
				β_{HML}			-0.045	-0.043
				t-stat.			*-0.89*	*-0.85*
				β_{MOM}				0.007
				t-stat.				*0.44*

Panel B: Business cycle variables predicted by FVIX factor returns

	-12	-9	-6	-3	0	3	6	9	12
NBER	5.234	5.245	8.175	7.688	3.954	-0.206	-0.427	1.145	1.134
t-stat.	*2.22*	*2.13*	*2.37*	*2.25*	*1.05*	*-0.05*	*-0.12*	*0.30*	*0.31*
VIX	0.066	0.270	0.495	0.749	1.748	-0.265	-0.088	0.024	-0.072
t-stat.	*0.23*	*0.92*	*1.70*	*2.33*	*5.09*	*-0.84*	*-0.26*	*0.08*	*-0.30*
TARCH	0.344	0.400	0.652	0.984	1.067	-0.208	-0.130	0.030	-0.006
t-stat.	*1.51*	*1.59*	*2.81*	*3.75*	*3.50*	*-0.78*	*-0.51*	*0.12*	*-0.03*
Realized	0.266	0.452	0.651	0.830	2.154	-0.035	-0.113	-0.016	-0.017
t-stat.	*0.75*	*1.02*	*1.72*	*1.78*	*4.09*	*-0.07*	*-0.23*	*-0.04*	*-0.05*

Table 2
Lottery-likeness, equity option-likeness, and firm-specific uncertainty

Panel A reports median values of several measures of firm-specific uncertainty – idiosyncratic volatility (IVol), analyst disagreement (Disp), analyst forecast error (Error), coefficient of variation of earnings (CVEarn), and cash flows (CVCFO) – across the quintiles formed from the sorts on the maximum daily return in the past month (Panel A1) and expected idiosyncratic skewness (Panel A2). Panel B reports, for the same quintiles, median values of growth options measures: market capitalization (Size), market-to-book (MB), the ratio of R&D expenses to total assets (R&D/TA), future sales growth (SG_{t+1}), and future investment growth (IG_{t+1}). Panel B also displays the measures of option-likeness created by risky debt: credit rating (Rating) and Ohlson's (1980) O-score, as well as the general measure of option-likeness from Grullon et al. (2012) – the convexity of the earnings-return relation (SUE flex). Credit rating is coded numerically as AAA=1, AA+=2, etc. Detailed definitions of all variables are in Appendix A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks with a per share price less than $5 on the portfolio formation date.

Panel A: Lottery-likeness and firm-specific uncertainty

A1. Past Maximum Returns

	Low	Max2	Max3	Max4	High	H-L	t(H-L)
IVol	0.984	1.465	1.920	2.504	3.751	2.767	29.2
Disp	2.885	3.420	4.178	5.331	7.315	4.429	21.3
Error	5.520	6.999	9.302	12.39	17.74	12.22	21.9
CVEarn	0.608	0.685	0.830	1.011	1.205	0.597	19.2
CVCFO	0.776	0.846	0.994	1.149	1.322	0.545	38.1

A2. Expected Skewness

	Low	ES2	ES3	ES4	High	H-L	t(H-L)
IVol	1.334	1.412	1.717	2.035	2.338	1.004	31.9
Disp	3.109	3.527	4.352	4.974	6.137	3.028	16.7
Error	5.655	6.753	8.979	11.50	14.42	8.770	21.3
CVEarn	0.528	0.690	0.901	1.086	1.259	0.731	35.0
CVCFO	0.626	0.703	0.938	1.178	1.494	0.867	37.1

Panel B: Lottery-likeness and option-likeness

B1. Past Maximum Returns

	Low	Max2	Max3	Max4	High	H-L	t(H-L)
Size	0.906	0.621	0.417	0.295	0.205	-0.702	-7.72
MB	1.853	1.880	1.892	1.960	2.088	0.235	3.16
R&D/TA	0.020	0.024	0.030	0.046	0.068	0.048	12.4
SG_{t+1}	0.067	0.085	0.102	0.122	0.143	0.076	11.9
IG_{t+1}	0.066	0.097	0.127	0.161	0.182	0.116	6.49
Rating	8.119	8.976	10.651	12.329	13.400	5.281	41.5
O-score	-1.961	-1.939	-1.799	-1.599	-1.119	0.842	21.8
SUE flex	0.054	0.060	0.078	0.099	0.121	0.067	13.5

B2. Expected Skewness

	Low	ES2	ES3	ES4	High	H-L	t(H-L)
Size	2.456	1.771	0.419	0.242	0.071	-2.385	-10.1
MB	2.183	2.031	1.679	1.619	1.618	-0.565	-13.2
R&D/TA	0.028	0.024	0.027	0.036	0.040	0.012	4.32
SG_{t+1}	0.067	0.064	0.072	0.083	0.095	0.028	11.9
IG_{t+1}	0.061	0.056	0.077	0.103	0.143	0.083	9.78
Rating	7.451	8.356	10.978	13.022	13.803	6.351	42.6
O-score	-2.220	-2.099	-1.905	-1.669	-1.256	0.965	18.0
SUE flex	0.039	0.040	0.062	0.118	0.218	0.179	17.5

Table 3

Lottery-likeness, aggregate volatility risk, and the cross-section of returns

The table reports value-weighted alphas from the CAPM, Fama-French (FF), and Carhart models, as well as alphas and FVIX betas from the those models augmented with FVIX (ICAPM, FF4, and Carhart5, respectively). The models are fitted to the quintile portfolios sorted on maximum daily return in the past month (Panel A) and expected idiosyncratic skewness (Panel B). FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Detailed definitions of all variables are in Appendix A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks with a per share price less than $5 on the portfolio formation date.

Panel A: Past maximum returns							*Panel B: Expected skewness*						
	Low	Max2	Max3	Max4	High	L-H		Low	ES2	ES3	ES4	High	L-H
α_{CAPM}	0.253	0.070	0.030	-0.234	-0.700	0.953	α_{CAPM}	0.147	0.018	-0.268	-0.118	-0.276	0.423
t-stat.	*2.94*	*1.04*	*0.38*	*-2.13*	*-3.34*	*3.40*	t-stat.	*1.69*	*0.29*	*-2.36*	*-0.89*	*-1.57*	*1.82*
α_{ICAPM}	-0.017	-0.081	0.084	0.103	0.004	-0.022	α_{ICAPM}	-0.058	-0.034	-0.089	0.217	0.252	-0.310
t-stat.	*-0.22*	*-1.04*	*0.99*	*0.96*	*0.02*	*-0.07*	t-stat.	*-0.57*	*-0.47*	*-0.71*	*1.30*	*1.06*	*-0.99*
β_{FVIX}	-0.593	-0.333	0.118	0.740	1.548	-2.141	β_{FVIX}	-0.427	-0.108	0.372	0.696	1.098	-1.525
t-stat.	*-3.53*	*-2.75*	*1.38*	*4.11*	*3.06*	*-3.20*	t-stat.	*-2.49*	*-1.10*	*3.59*	*3.81*	*3.30*	*-3.08*
α_{FF}	0.180	0.028	0.023	-0.189	-0.543	0.723	α_{FF}	0.106	0.005	-0.237	-0.117	-0.234	0.340
t-stat.	*2.59*	*0.54*	*0.30*	*-1.87*	*-3.30*	*3.36*	t-stat.	*1.71*	*0.07*	*-2.07*	*-1.03*	*-1.80*	*2.21*
α_{FF4}	0.013	-0.061	0.053	0.014	-0.175	0.188	α_{FF4}	0.020	-0.020	-0.161	-0.072	-0.087	0.108
t-stat.	*0.21*	*-1.13*	*0.63*	*0.15*	*-1.08*	*0.91*	t-stat.	*0.32*	*-0.29*	*-1.23*	*-0.54*	*-0.58*	*0.63*
β_{FVIX}	-0.383	-0.203	0.067	0.465	0.843	-1.227	β_{FVIX}	-0.183	-0.053	0.162	0.096	0.312	-0.495
t-stat.	*-4.71*	*-4.12*	*0.99*	*3.69*	*3.72*	*-4.14*	t-stat.	*-2.33*	*-0.70*	*1.84*	*0.82*	*2.32*	*-2.89*
$\alpha_{Carhart}$	0.093	0.005	0.074	-0.142	-0.452	0.545	$\alpha_{Carhart}$	0.118	0.092	-0.099	0.011	-0.175	0.293
t-stat.	*1.23*	*0.10*	*0.79*	*-1.35*	*-2.64*	*2.42*	t-stat.	*1.90*	*1.58*	*-0.94*	*0.10*	*-1.27*	*1.89*
$\alpha_{Carhart5}$	-0.081	-0.086	0.106	0.066	-0.074	-0.007	$\alpha_{Carhart5}$	0.031	0.075	-0.008	0.070	-0.019	0.049
t-stat.	*-1.26*	*-1.75*	*1.14*	*0.71*	*-0.46*	*-0.04*	t-stat.	*0.51*	*1.19*	*-0.06*	*0.60*	*-0.12*	*0.30*
β_{FVIX}	-0.393	-0.206	0.073	0.471	0.854	-1.248	β_{FVIX}	-0.181	-0.035	0.190	0.122	0.325	-0.505
t-stat.	*-4.76*	*-4.06*	*1.24*	*3.78*	*3.73*	*-4.17*	t-stat.	*-2.36*	*-0.48*	*2.14*	*1.06*	*2.46*	*-2.94*

Table 4
Lottery-likeness, option-likeness,

and aggregate volatility risk

Panel A1 reports value-weighted alphas from the CAPM, Fama-French (FF), and Carhart models, as well as alphas and FVIX betas from the those models augmented with FVIX (ICAPM, FF4, and Carhart5, respectively) for the arbitrage portfolios that buy firms with low values of the maximum daily return in the previous month and short firms with high values of maximum daily return in the past month. The arbitrage portfolios are formed separately in each market-to-book quintile. Panel A2 repeats Panel A1 replacing the low-minus-high maximum return portfolio by the portfolio that buys firms with low and shorts firms with high expected idiosyncratic skewness. Panel B repeats the analysis in Panel A using credit rating instead of market-to-book. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Detailed definitions of all variables are in Appendix A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks with a per share price less than \$5 on the portfolio formation date.

Panel A: Maximum/skewness effect, growth options, and aggregate volatility risk

A1: Maximum effect / *A2: Skewness effect*

	Value	Neut	Growth	G-V		Value	Neut	Growth	G-V
α_{CAPM}	0.362	0.750	1.007	0.645	α_{CAPM}	-0.047	0.264	0.578	0.625
t-stat.	*1.14*	*3.02*	*2.98*	*2.10*	t-stat.	*-0.43*	*1.84*	*3.14*	*4.05*
α_{ICAPM}	-0.103	0.264	0.064	0.167	α_{ICAPM}	-0.225	-0.145	-0.033	0.192
t-stat.	*-0.34*	*1.04*	*0.21*	*0.50*	t-stat.	*-1.67*	*-0.79*	*-0.13*	*1.04*
β_{FVIX}	-1.022	-1.067	-2.072	-1.050	β_{FVIX}	-0.391	-0.897	-1.341	-0.951
t-stat.	*-2.81*	*-2.34*	*-4.24*	*-3.17*	t-stat.	*-2.30*	*-3.51*	*-3.35*	*-3.54*
α_{FF}	0.294	0.633	0.816	0.522	α_{FF}	0.136	0.127	0.608	0.471
t-stat.	*1.00*	*3.00*	*2.99*	*1.68*	t-stat.	*0.64*	*0.55*	*2.85*	*1.75*
α_{FF4}	0.069	0.429	0.280	0.211	α_{FF4}	0.130	-0.086	0.366	0.235
t-stat.	*0.25*	*1.85*	*1.09*	*0.64*	t-stat.	*0.59*	*-0.34*	*1.62*	*0.84*
β_{FVIX}	-0.517	-0.467	-1.229	-0.712	β_{FVIX}	-0.014	-0.487	-0.555	-0.542
t-stat.	*-1.61*	*-1.40*	*-5.07*	*-2.48*	t-stat.	*-0.06*	*-2.85*	*-2.46*	*-2.13*
$\alpha_{Carhart}$	0.031	0.309	0.588	0.557	$\alpha_{Carhart}$	-0.128	-0.128	0.394	0.522
t-stat.	*0.08*	*1.48*	*2.06*	*1.64*	t-stat.	*-0.58*	*-0.52*	*1.70*	*1.69*
$\alpha_{Carhart5}$	-0.212	0.086	0.032	0.244	$\alpha_{Carhart5}$	-0.147	-0.356	0.137	0.285
t-stat.	*-0.62*	*0.38*	*0.13*	*0.65*	t-stat.	*-0.63*	*-1.34*	*0.60*	*0.92*
β_{FVIX}	-0.547	-0.505	-1.256	-0.709	β_{FVIX}	-0.044	-0.516	-0.580	-0.536
t-stat.	*-1.78*	*-1.59*	*-5.06*	*-2.45*	t-stat.	*-0.21*	*-3.46*	*-2.79*	*-2.12*

Panel B: Maximum/skewness effect, O-score, and aggregate volatility risk

B1: Maximum effect

	Low O	Medium	High O	H-L
α_{CAPM}	0.353	0.478	1.027	0.674
t-stat.	*1.34*	*2.52*	*3.28*	*2.79*
α_{ICAPM}	-0.186	-0.070	-0.002	0.183
t-stat.	*-0.79*	*-0.31*	*-0.01*	*0.65*
β_{FVIX}	-1.184	-1.204	-2.261	-1.077
t-stat.	*-2.70*	*-3.45*	*-4.13*	*-3.27*
α_{FF}	0.147	0.329	0.839	0.692
t-stat.	*0.73*	*1.89*	*3.12*	*2.71*
α_{FF4}	-0.126	0.075	0.189	0.315
t-stat.	*-0.56*	*0.43*	*0.77*	*1.23*
β_{FVIX}	-0.627	-0.581	-1.489	-0.863
t-stat.	*-2.18*	*-3.26*	*-5.61*	*-3.59*
$\alpha_{Carhart}$	-0.067	0.105	0.523	0.590
t-stat.	*-0.33*	*0.63*	*1.61*	*1.98*
$\alpha_{Carhart5}$	-0.356	-0.164	-0.152	0.203
t-stat.	*-1.60*	*-0.98*	*-0.55*	*0.68*
β_{FVIX}	-0.652	-0.607	-1.527	-0.875
t-stat.	*-2.39*	*-3.78*	*-5.44*	*-3.43*

B2: Skewness effect

	Low O	Medium	High O	H-L
α_{CAPM}	-0.029	0.321	0.681	0.711
t-stat.	*-0.15*	*1.51*	*2.79*	*2.49*
α_{ICAPM}	-0.260	-0.098	0.086	0.347
t-stat.	*-1.20*	*-0.41*	*0.33*	*1.32*
β_{FVIX}	-0.480	-0.872	-1.238	-0.757
t-stat.	*-2.02*	*-4.24*	*-4.59*	*-3.75*
α_{FF}	-0.022	0.295	0.598	0.619
t-stat.	*-0.13*	*1.64*	*3.07*	*2.45*
α_{FF4}	0.072	0.180	0.282	0.210
t-stat.	*0.41*	*1.02*	*1.38*	*0.85*
β_{FVIX}	0.199	-0.246	-0.673	-0.872
t-stat.	*0.94*	*-1.69*	*-4.82*	*-3.85*
$\alpha_{Carhart}$	-0.036	0.092	0.426	0.462
t-stat.	*-0.23*	*0.47*	*2.30*	*1.83*
$\alpha_{Carhart5}$	0.058	-0.046	0.084	0.025
t-stat.	*0.35*	*-0.23*	*0.45*	*0.10*
β_{FVIX}	0.196	-0.288	-0.710	-0.907
t-stat.	*0.92*	*-2.37*	*-4.97*	*-4.06*

Table 5
Past minimum returns, equity option-likeness,

and firm-specific uncertainty

Panel A reports median values of several measures of firm-specific uncertainty from Table 2 across the quintiles formed from sorts on the minimum daily return in the past month. The minimum return is multiplied by -1 and then orthogonalized to maximum return in the same month by running, each month, a cross-sectional regression of minimum returns on maximum returns and taking the residual (RMin). Panel B reports, for the same quintiles, median values of growth options measures from Table 2, as well as the measures of option-likeness created by risky debt and the general measure of option-likeness from Grullon et al. (2012). Credit rating is coded numerically as AAA=1, AA+=2, etc. Detailed definitions of all variables are in Appendix A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks with a per share price less than $5 on the portfolio formation date.

Panel A. Residual minimum return and firm-specific uncertainty

	Low	RMin2	RMin3	RMin4	High	H-L	t(H-L)
IVol	1.401	1.402	1.734	2.197	3.178	1.777	34.9
Disp	3.462	3.402	3.987	4.896	6.252	2.789	15.3
Error	6.844	6.863	8.516	11.37	16.77	9.925	19.0
CVEarn	0.761	0.711	0.819	0.954	1.072	0.310	10.1
CVCFO	0.925	0.865	0.962	1.092	1.229	0.304	26.6

Panel B: Residual minimum return and option-likeness

	Low	RMin2	RMin3	RMin4	High	H-L	t(H-L)
Size	0.658	0.644	0.447	0.319	0.239	-0.419	-7.07
MB	1.877	1.890	1.881	1.907	2.058	0.181	3.19
R&D/TA	0.027	0.026	0.030	0.041	0.057	0.030	11.2
SG_{t+1}	0.089	0.087	0.096	0.108	0.121	0.031	6.83
IG_{t+1}	0.103	0.100	0.121	0.140	0.154	0.050	4.49
Rating	9.046	8.863	9.976	11.546	12.700	3.654	39.0
O-score	-1.769	-1.897	-1.795	-1.634	-1.385	0.385	11.1
SUEflex	0.071	0.063	0.070	0.091	0.111	0.039	7.42

Panel C: Residual minimum return and lottery-likeness

	Low	RMin2	RMin3	RMin4	High	H-L	t(H-L)
Max	0.070	0.048	0.053	0.061	0.077	0.007	10.4
Min	0.025	0.032	0.042	0.057	0.102	0.077	41.1
TopMax	0.159	0.051	0.055	0.074	0.157	-0.002	-0.59
TopMin	0.006	0.002	0.004	0.016	0.468	0.462	247.5

Table 6
Minimum effect and its cross-section

Panel A reports value-weighted alphas from the CAPM, Fama-French (FF), and Carhart models, as well as alphas and FVIX betas from the those models augmented with FVIX (ICAPM, FF4, and Carhart5, respectively). The models are fitted to the quintile portfolios sorted on the minimum daily return in the past month. The minimum return is multiplied by -1 and then orthogonalized to maximum return in the same month by running, each month, a cross-sectional regression of minimum returns on maximum returns and taking the residual (RMin). Panel B reports value-weighted alphas from the same models for the arbitrage portfolios that buy low RMin firms and short high RMin firms. The arbitrage portfolios are formed separately in each market-to-book (Panel B1) or O-score (Panel B2) group (top 30%, middle 40%, bottom 30%). FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Detailed definitions of all variables are in Appendix A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks with a per share price less than $5 on the portfolio formation date.

Panel A: Minimum effect

	Low	RMin2	RMin3	RMin4	High	L-H
α_{CAPM}	0.071	0.055	0.125	-0.009	-0.634	0.705
t-stat.	*0.91*	*1.09*	*2.20*	*-0.10*	*-4.03*	*3.42*
α_{ICAPM}	-0.077	-0.077	0.079	0.143	-0.192	0.114
t-stat.	*-0.92*	*-1.70*	*1.44*	*1.51*	*-1.21*	*0.53*
β_{FVIX}	-0.327	-0.291	-0.101	0.335	0.972	-1.299
t-stat.	*-3.72*	*-3.42*	*-1.78*	*2.56*	*4.50*	*-4.72*
α_{FF}	0.047	0.023	0.100	0.007	-0.568	0.615
t-stat.	*0.60*	*0.51*	*1.65*	*0.08*	*-3.71*	*3.06*
α_{FF4}	-0.043	-0.057	0.068	0.064	-0.340	0.297
t-stat.	*-0.56*	*-1.19*	*1.29*	*0.72*	*-2.40*	*1.62*
β_{FVIX}	-0.206	-0.185	-0.073	0.130	0.523	-0.729
t-stat.	*-2.73*	*-3.78*	*-1.13*	*1.09*	*3.73*	*-4.32*
$\alpha_{Carhart}$	0.010	-0.014	0.088	0.031	-0.426	0.436
t-stat.	*0.13*	*-0.25*	*1.30*	*0.35*	*-2.62*	*2.08*
$\alpha_{Carhart5}$	-0.083	-0.098	0.055	0.089	-0.187	0.104
t-stat.	*-1.10*	*-1.69*	*0.91*	*0.96*	*-1.34*	*0.56*
β_{FVIX}	-0.210	-0.190	-0.075	0.133	0.540	-0.750
t-stat.	*-2.81*	*-3.80*	*-1.15*	*1.12*	*4.34*	*-4.95*

Panel B: Minimum effect and equity option-likeness

B1: Growth options | *B2: O-score*

	Value	Neut	Growth	G-V		Low O	Medium	High O	H-L
α_{CAPM}	0.173	0.213	0.692	0.519	α_{CAPM}	0.156	0.133	0.801	0.645
t-stat.	*0.74*	*0.94*	*2.92*	*1.94*	t-stat.	*0.65*	*0.74*	*2.54*	*2.27*
α_{ICAPM}	-0.037	-0.274	0.207	0.244	α_{ICAPM}	-0.127	-0.214	0.130	0.258
t-stat.	*-0.16*	*-1.05*	*0.88*	*0.87*	t-stat.	*-0.59*	*-0.91*	*0.49*	*1.07*
β_{FVIX}	-0.462	-1.069	-1.065	-0.604	β_{FVIX}	-0.622	-0.762	-1.473	-0.851
t-stat.	*-1.73*	*-4.08*	*-4.01*	*-2.40*	t-stat.	*-2.03*	*-2.50*	*-4.09*	*-4.34*
α_{FF}	0.136	0.127	0.608	0.471	α_{FF}	0.024	0.072	0.657	0.633
t-stat.	*0.64*	*0.55*	*2.85*	*1.75*	t-stat.	*0.12*	*0.41*	*2.43*	*2.25*
α_{FF4}	0.130	-0.086	0.366	0.235	α_{FF4}	-0.049	-0.059	0.251	0.300
t-stat.	*0.59*	*-0.34*	*1.62*	*0.84*	t-stat.	*-0.23*	*-0.33*	*1.00*	*1.22*
β_{FVIX}	-0.014	-0.487	-0.555	-0.542	β_{FVIX}	-0.168	-0.301	-0.930	-0.763
t-stat.	*-0.06*	*-2.85*	*-2.46*	*-2.13*	t-stat.	*-0.73*	*-1.64*	*-3.75*	*-3.98*
$\alpha_{Carhart}$	-0.128	-0.128	0.394	0.522	$\alpha_{Carhart}$	-0.160	-0.038	0.382	0.541
t-stat.	*-0.58*	*-0.52*	*1.70*	*1.69*	t-stat.	*-0.78*	*-0.22*	*1.25*	*1.73*
$\alpha_{Carhart5}$	-0.147	-0.356	0.137	0.285	$\alpha_{Carhart5}$	-0.243	-0.176	-0.044	0.199
t-stat.	*-0.63*	*-1.34*	*0.60*	*0.92*	t-stat.	*-1.16*	*-0.99*	*-0.16*	*0.75*
β_{FVIX}	-0.044	-0.516	-0.580	-0.536	β_{FVIX}	-0.189	-0.314	-0.962	-0.774
t-stat.	*-0.21*	*-3.46*	*-2.79*	*-2.12*	t-stat.	*-0.89*	*-1.80*	*-4.06*	*-3.98*

Table 7
Volatility risk vs. lottery-likeness in portfolio-level cross-sectional regressions

The table presents the results of cross-sectional portfolio regressions run each month: in Panel A, the base assets are the five-by-five sorts on size and market-to-book and in Panel B, the base assets are the five-by-five sorts on market-to-book and one of the three lottery-likeness measures: maximum return (Max, columns one to three), minimum return times -1 (Min, columns four to six), and expected skewness (ESkew, columns seven to nine). The regressions run, within each month, the future portfolio returns on the lottery-likeness measures, FVIX beta, and controls. The controls are market beta (Beta), log size, market-to-book (MB), cumulative return between months t-2 and t-12 (MOM), and return in the past month (REV). The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks priced below $5 at the portfolio formation date.

Panel A: Volatility risk vs. lottery effects in size-MB sorts

	1	2	3	4	5	6	7
Beta	0.545	0.448	0.627	0.423	0.534	0.107	0.354
t-stat.	*1.73*	*1.32*	*1.96*	*1.29*	*1.78*	*0.33*	*1.21*
lnSize	-0.037	-0.068	-0.078	-0.065	-0.078	-0.104	-0.105
t-stat.	*-0.77*	*-1.41*	*-1.44*	*-1.45*	*-1.57*	*-1.95*	*-1.83*
lnMB	-0.009	-0.011	-0.001	-0.022	-0.007	-0.010	-0.001
t-stat.	*-0.34*	*-0.42*	*-0.03*	*-0.83*	*-0.26*	*-0.40*	*-0.03*
Mom	0.596	0.644	0.433	1.096	0.774	0.691	0.383
t-stat.	*1.15*	*1.27*	*0.80*	*2.30*	*1.47*	*1.48*	*0.75*
Rev	-0.014	-0.007	-0.013	-0.025	-0.019	-0.012	-0.018
t-stat.	*-0.79*	*-0.41*	*-0.65*	*-1.43*	*-1.03*	*-0.71*	*-0.97*
FVIX	-0.857		-0.969		-0.830		-0.601
t-stat.	*-1.87*		*-2.10*		*-1.94*		*-1.40*
Max		-11.32	-5.534				
t-stat.		*-2.26*	*-1.00*				
Min				-10.45	-4.749		
t-stat.				*-1.74*	*-0.70*		
ESkew						-0.632	-0.434
t-stat.						*-2.31*	*-1.51*

Panel B: Volatility risk vs. lottery effects in lottery-MB sorts

	Max/MB Sorts			Min/MB Sorts			ESkew/MB Sorts		
	1	2	3	4	5	6	7	8	9
Beta	0.553	0.508	0.647	0.470	0.417	0.412	0.496	0.470	0.607
t-stat.	*1.98*	*1.73*	*2.37*	*1.72*	*1.40*	*1.57*	*1.54*	*1.45*	*1.84*
lnSize	-0.011	0.047	-0.037	-0.044	-0.008	-0.094	-0.091	-0.076	-0.162
t-stat.	*-0.16*	*0.73*	*-0.52*	*-0.62*	*-0.11*	*-1.24*	*-1.53*	*-0.95*	*-1.79*
lnMB	-0.146	-0.226	-0.114	-0.048	-0.163	0.008	-0.063	-0.102	0.029
t-stat.	*-1.32*	*-2.29*	*-1.02*	*-0.43*	*-1.52*	*0.07*	*-0.58*	*-1.01*	*0.24*
Mom	0.698	1.241	1.132	1.044	1.248	1.141	0.125	0.491	0.160
t-stat.	*1.56*	*2.89*	*2.38*	*2.39*	*3.24*	*2.71*	*0.22*	*0.79*	*0.27*
Rev	-0.011	-0.006	-0.018	0.000	-0.014	-0.014	0.010	0.000	0.005
t-stat.	*-0.71*	*-0.38*	*-1.05*	*-0.02*	*-1.00*	*-0.93*	*0.60*	*0.00*	*0.29*
FVIX	-0.865		-1.004	-0.838		-0.763	-0.833		-1.022
t-stat.	*-2.19*		*-2.57*	*-2.14*		*-2.02*	*-1.74*		*-2.07*
Max		-6.580	-2.742						
t-stat.		*-1.96*	*-0.75*						
Min					-8.183	-4.027			
t-stat.					*-1.94*	*-0.87*			
ESkew								-0.454	-0.251
t-stat.								*-1.68*	*-1.02*

Table 8

Volatility risk vs. lottery-likeness in firm-level cross-sectional regressions

The table presents the results of cross-sectional firm-level regressions run each month. Panel A uses the same independent variables as Table 7, while Panel B creates dummies for the top FVIX beta (Max, Min, Skew) quintile and replaces the respective continuous variable by the top quintile dummy. The control variables in Panel B (untransformed) are the same as in Panel A. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks priced below $5 at the portfolio formation date.

Panel A: Untransformed lottery variables and FVIX betas

	1	2	3	4	5	6	7
Beta	0.186	0.178	0.202	0.177	0.206	0.169	0.219
t-stat.	*1.60*	*1.47*	*1.87*	*1.45*	*1.90*	*1.13*	*1.77*
lnSize	-0.105	-0.111	-0.127	-0.114	-0.129	-0.132	-0.148
t-stat.	*-2.19*	*-2.71*	*-2.91*	*-2.76*	*-2.97*	*-3.02*	*-3.27*
lnMB	-0.050	-0.054	-0.046	-0.056	-0.047	-0.035	-0.023
t-stat.	*-3.28*	*-4.01*	*-3.24*	*-4.06*	*-3.26*	*-2.34*	*-1.51*
Mom	0.463	0.504	0.439	0.499	0.441	0.456	0.365
t-stat.	*2.08*	*2.52*	*2.11*	*2.50*	*2.12*	*2.14*	*1.65*
Rev	-0.037	-0.033	-0.035	-0.042	-0.043	-0.039	-0.041
t-stat.	*-7.35*	*-6.63*	*-6.51*	*-9.73*	*-9.29*	*-8.38*	*-7.91*
FVIX	-0.258		-0.271		-0.277		-0.324
t-stat.	*-1.82*		*-2.03*		*-2.07*		*-2.10*
Max		-3.813	-3.379				
t-stat.		*-3.31*	*-2.79*				
Min				-5.688	-5.186		
t-stat.				*-3.74*	*-3.29*		
ESkew						-0.302	-0.252
t-stat.						*-3.32*	*-2.76*

Panel B: Top quintile dummies

	1	2	3	4	5	6	7
Beta	0.127	0.076	0.039	0.079	0.043	0.073	0.036
t-stat.	*3.29*	*0.55*	*1.24*	*0.57*	*1.33*	*0.45*	*1.05*
lnSize	-0.503	-0.033	-0.190	-0.040	-0.200	-0.052	-0.174
t-stat.	*-12.6*	*-0.96*	*-5.27*	*-1.15*	*-5.57*	*-1.39*	*-4.61*
lnMB	0.024	-0.045	-0.010	-0.044	-0.009	-0.017	0.006
t-stat.	*1.46*	*-3.15*	*-0.69*	*-3.08*	*-0.57*	*-1.12*	*0.43*
Mom	-0.604	0.660	0.154	0.656	0.135	0.476	0.045
t-stat.	*-2.51*	*3.84*	*0.81*	*3.78*	*0.70*	*2.55*	*0.22*
Rev	-0.039	-0.023	-0.032	-0.030	-0.030	-0.026	-0.030
t-stat.	*-7.21*	*-5.00*	*-6.48*	*-7.04*	*-6.61*	*-5.44*	*-6.24*
HiFVIX	-0.377		-0.158		-0.167		-0.186
t-stat.	*-5.34*		*-2.68*		*-2.82*		*-2.88*
HiMax		-0.385	0.183				
t-stat.		*-3.86*	*1.69*				
HiMin				-0.514	0.009		
t-stat.				*-6.01*	*0.09*		
HiSkew						-0.153	0.056
t-stat.						*-1.95*	*0.73*

Table 9

FVIX pricing and lottery-likeness

The table presents the CAPM, Fama-French (FF), and Carhart alphas of the quintile portfolios sorted on historical FVIX betas. The FVIX betas are from the two-factor ICAPM with the market factor and FVIX. Panel A performs the sorts without controlling for any other characteristics. The other panels (B–D) control for one lottery-likeness characteristic at a time (indicated in the name of the panel) by sorting on the residual from a cross-sectional regression (run each month) of the historical FVIX beta on the lottery-likeness characteristic. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks priced below $5 at the portfolio formation date.

A: FVIX beta sorts, unconditional

	Low	FVIX2	FVIX3	FVIX4	High	L-H
α_{CAPM}	0.067	0.198	0.192	0.034	-0.613	0.680
t-stat.	*0.45*	*1.48*	*1.30*	*0.25*	*-3.65*	*4.20*
α_{FF}	-0.018	0.104	0.093	-0.038	-0.555	0.538
t-stat.	*-0.19*	*1.33*	*1.12*	*-0.57*	*-5.72*	*3.72*
$\alpha_{Carhart}$	0.070	0.143	0.131	0.042	-0.341	0.411
t-stat.	*0.80*	*1.99*	*1.65*	*0.66*	*-2.84*	*2.60*

C: FVIX beta orthogonalized to past maximum return

	Low	FVIX2	FVIX3	FVIX4	High	L-H
α_{CAPM}	0.054	0.197	0.181	0.118	-0.496	0.550
t-stat.	*0.36*	*1.51*	*1.28*	*0.80*	*-3.06*	*3.93*
α_{FF}	-0.018	0.108	0.087	0.034	-0.450	0.431
t-stat.	*-0.21*	*1.51*	*1.10*	*0.49*	*-5.06*	*3.26*
$\alpha_{Carhart}$	0.058	0.148	0.114	0.080	-0.304	0.362
t-stat.	*0.71*	*2.13*	*1.54*	*1.25*	*-2.88*	*2.62*

B: FVIX beta orthogonalized to expected skewness

	Low	FVIX2	FVIX3	FVIX4	High	L-H
α_{CAPM}	0.201	0.133	0.216	0.101	-0.386	0.588
t-stat.	*1.73*	*1.60*	*2.62*	*1.29*	*-2.19*	*2.25*
α_{FF}	0.125	0.073	0.152	0.095	-0.327	0.453
t-stat.	*1.34*	*1.13*	*2.15*	*1.17*	*-1.80*	*1.86*
$\alpha_{Carhart}$	0.120	0.107	0.081	0.139	-0.262	0.382
t-stat.	*1.36*	*1.51*	*1.18*	*1.38*	*-1.63*	*1.75*

D: FVIX beta orthogonalized to past minimum return

	Low	FVIX2	FVIX3	FVIX4	High	L-H
α_{CAPM}	0.036	0.181	0.221	0.099	-0.483	0.519
t-stat.	*0.24*	*1.38*	*1.57*	*0.67*	*-2.96*	*3.72*
α_{FF}	-0.036	0.091	0.128	0.018	-0.438	0.402
t-stat.	*-0.43*	*1.24*	*1.69*	*0.24*	*-4.89*	*3.08*
$\alpha_{Carhart}$	0.058	0.131	0.153	0.056	-0.301	0.359
t-stat.	*0.70*	*1.91*	*2.08*	*0.83*	*-2.81*	*2.55*

Table 10
Lottery-likeness and volatility risk

The table presents the CAPM, Fama-French (FF), and Carhart alphas of the quintile portfolios sorted on lottery-likeness characteristics (indicated in the name of the panel). The sorts are on the residual from a cross-sectional regression (run each month) of the lottery-likeness characteristic on the historical FVIX beta. The FVIX betas are from the two-factor ICAPM with the market factor and FVIX. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2015. The sample excludes stocks priced below $5 at the portfolio formation date.

A: Past Maximum Return Sorts, Conditional on FVIX Beta

	Low	Max2	Max3	Max4	High	L-H
α_{CAPM}	0.033	0.016	0.063	-0.043	-0.294	0.327
t-stat.	*0.40*	*0.26*	*1.07*	*-0.44*	*-2.55*	*1.96*
α_{FF}	0.013	-0.023	0.041	-0.091	-0.258	0.271
t-stat.	*0.15*	*-0.44*	*0.73*	*-1.05*	*-2.53*	*1.75*
$\alpha_{Carhart}$	-0.007	-0.068	0.029	-0.034	-0.089	0.082
t-stat.	*-0.08*	*-1.32*	*0.46*	*-0.40*	*-0.84*	*0.49*

B: Expected Skewness Sorts, Conditional on FVIX Beta

	Low	ES2	ES3	ES4	High	L-H
α_{CAPM}	0.097	0.103	0.120	-0.068	-0.046	0.143
t-stat.	*1.50*	*1.33*	*1.43*	*-0.67*	*-0.40*	*0.89*
α_{FF}	0.106	0.049	0.045	-0.069	-0.031	0.138
t-stat.	*1.83*	*0.78*	*0.64*	*-0.72*	*-0.35*	*1.10*
$\alpha_{Carhart}$	0.072	0.078	0.107	0.055	0.012	0.061
t-stat.	*1.18*	*1.13*	*1.52*	*0.57*	*0.13*	*0.46*

C: Past Minimum Return Sorts, Conditional on FVIX Beta

	Low	Min2	Min3	Min4	High	L-H
α_{CAPM}	0.100	0.026	-0.057	0.022	-0.125	0.225
t-stat.	*1.20*	*0.50*	*-0.78*	*0.29*	*-1.14*	*1.38*
α_{FF}	0.076	0.001	-0.105	-0.018	-0.100	0.176
t-stat.	*0.94*	*0.02*	*-1.63*	*-0.27*	*-0.99*	*1.18*
$\alpha_{Carhart}$	0.006	-0.033	-0.092	0.011	0.084	-0.077
t-stat.	*0.08*	*-0.57*	*-1.33*	*0.16*	*0.81*	*-0.50*