Asset prices and “the devil(s) you know”

Asset Prices and “the Devil(s) You Know”*

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Abstract

In this paper, we study the asset pricing implications of persistence in the risk-neutral return distribution’s central moments. We detect a both economically and statistically significant premium of stocks with low over stocks with high such persistence. Annual value-weighted excess (risk-adjusted) returns are 4.38% (3.06%). These results cannot be explained by factors and characteristics documented in the previous literature. Furthermore, it is not the persistence of only one of the individual distributional moments but rather the joint persistence in *all* central moments of the risk-neutral distribution that is priced.

JEL classification: G12, G11, G10

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I Introduction

"Better the devil you know than the devil you don't."

In this paper, we test the asset pricing implications of the persistence in a stock's return distribution. We measure this persistence with the degree of joint predictability of the option-implied distribution's central moments by their lagged values. Investors likely prefer stocks with a more persistent and, thus, more predictable distribution. They likely want to avoid holding stocks with low persistence in the distribution, i.e., those "devils" they know only little about. On the other hand, these stocks may provide attractive risk–return profiles for investors less concerned about how persistent their holdings' return distributions are.

We propose a novel measure that captures the persistence in the return distribution. To define this measure, we set up a vector autoregressive (VAR) model for the joint day-by-day predictability of the central moments (volatility, skewness, and kurtosis) of a stock's risk-neutral distribution. The main measure for persistence in the risk-neutral distribution's central moments is the likelihood ratio test statistic comparing the log-likelihood of this VAR(1) model to that of a simple constant model for the central moments.[1] Our main contribution, thus, lies in analyzing the asset pricing implications of the persistence of the risk-neutral return distribution's central moments.

First, we empirically test whether the persistence of the option-implied distribution's central moments is (i) related to other stock characteristics that drive the cross-section of stock returns and (ii) priced in the cross-section of U.S. stock returns. We show that persistence in the option-implied distribution's central moments is only weakly related to other variables. More importantly, we find that persistence of the option-implied distribution's central mo-

[1] Naturally, an investor is interested in predicting the real-world return distribution rather than its risk-neutral counterpart. However, first, risk-neutral moments are typically superior predictors for *future* realized moments than their physical counterparts. Second, we examine whether the measure of persistence is priced cross-sectionally, which materially facilitates the comparability of the predictability for the risk-neutral and physical distributions. We discuss these issues further below.

ments is strongly negatively priced in the stock market. Stocks with low persistence in the moments of the distribution earn an economically large and statistically significant annualized value-weighted return premium of 4.38% over stocks that exhibit a high persistence in the central moments of their risk-neutral return distribution. This return premium can only be partially explained by known risk factors. The Fama & French (2015) five-factor alpha amounts to a significant 3.01%.

Second, we examine whether the substantial long–short return when sorting on the persistence of option-implied moments can be related to previously documented factors and return anomalies. Double-sorts and Fama & MacBeth (1973) regressions reveal that none of these control variables can explain the related risk premium. The double-sorted portfolio returns and alphas all remain statistically significant and are of similar magnitudes to those of the univariate sort. In cross-sectional regressions, a two-standard deviation increase in the persistence of option-implied central moments leads to a decrease in annual returns of 2.5% when including control variables. In a regression with all control variables, the cross-sectional risk premium on the persistence of the option-implied central moments is significant relative to the rigorous criteria defined by Harvey et al. (2016). These results cannot be explained by a level-effect of the individual higher moments or potential measures of uncertainty proposed in previous studies.

Third, we examine the individual moments to investigate which of these is the driving force of the negative price of the joint persistence of the option-implied central moments. We find that none of the single moments can reproduce the results we obtain for the joint persistence of the option-implied moments. Thus, the combined persistence of *all* risk-neutral moments appears to be important.

We set up a battery of tests to examine the robustness of our main results. We obtain similar results for less frequent rebalancing and alternative holding periods. In addition, the results are similar for different horizons for the option-implied measures and alternative

VAR model specifications.

We use measures that characterize the risk-neutral rather than the physical return distribution even though investors are primarily concerned with the physical distribution. We do so, first, because risk-neutral moments are typically superior predictors for physical moments compared to their own lags (Navatte & Villa, 2000; Jiang & Tian, 2005; Shackleton et al., 2010). This holds especially for the second moment, but we show that it is the case also for the other higher return moments of the return distribution of individual stocks. Second, we study the cross-section of firm-specific persistence of the risk-neutral distribution's central moments and future stock returns. The risk-neutral probabilities are essentially real-world probabilities tilted toward bad states. Thus, risk-neutral moments might change if the physical distribution changes or if the mapping from real-world to risk-neutral probabilities changes. In the latter case, the moments for all stocks are equally unpredictable. Thus, in the cross-section, higher persistence of the central moments of the risk-neutral distribution should be associated with higher persistence of the physical distribution. Changes in the mapping between the two measures should only yield more noise in our main measure and, thus, make it less likely to detect a significant impact on the cross-section of stock returns.

Our paper contributes to several strands of the literature. Baltussen et al. (2018) examine the relation of volatility-of-volatility and future stock returns, interpreting volatility-of-volatility as a measure of uncertainty. Hollstein & Prokopczuk (2018) further show that aggregate volatility-of-volatility is priced in the cross-section of stock returns. There are several important differences between our study and those of Baltussen et al. (2018) and Hollstein & Prokopczuk (2018). First, while these studies focus on volatility, we examine the persistence of volatility, skewness, and kurtosis in a joint setting. This is important since investors do not only care about volatility but also about higher moments of the distribution. Furthermore, we find that there are cross-moment linkages, especially between volatility and kurtosis in the VAR(1) model. Second, volatility and persistence are not direct antipodes.

If it is not plain noise but predictable variation that causes volatility, then persistence will be high even though a time-series is volatile. Conversely, if a time-series of volatility is close to constant, both the volatility-of-volatility and our measure of persistence will be very low. We find that the former two cases, in various shades, occur frequently: empirically volatility-of-volatility displays only little correlation with our measure of the joint moment persistence. Third, we find that the persistence in the option-implied central moments is significantly priced even after explicitly controlling for volatility-of-volatility.

Further studies examining uncertainty in an asset pricing context are Zhang (2006), Anderson et al. (2009), Bossaerts et al. (2010), and Bali & Zhou (2016). However, these studies are only mildly related to ours and we find that the persistence of the option-implied central moments is priced in the cross-section of stock returns even after controlling for several potential measures of uncertainty.

We also contribute to the literature on the predictability of risk-neutral moments. Panigirtzoglou & Skiadopoulos (2004), Goncalves & Guidolin (2006), and Lynch & Panigirtzoglou (2008) study the dynamics of option-implied moments and densities for index options. Neumann & Skiadopoulos (2013) study the predictability of the higher moments of the S&P 500 index, finding that higher moments are generally predictable. We find that the risk-neutral central moments of individual stocks are also generally predictable in-sample. More importantly, we show that the degree of predictability of the moments, i.e., their persistence, is related to future stock returns.

Our paper connects to the literature on higher moments and portfolio allocation. The literature emphasizes the importance of higher moments for stock returns and asset allocation (Samuelson, 1970; Arditti & Levy, 1975; Harvey & Siddique, 1999). While the interest has initially been in co-moments (coskewness and to a lesser extent cokurtosis) – e.g., Harvey & Siddique (2000) and Smith (2007) – recent studies find that firm-specific skewness is an important determinant of asset prices – e.g., Brunnermeier & Parker (2005), Barberis

& Huang (2008), and Boyer et al. (2009). Therefore, we follow the latter stream of the literature and examine the persistence of the moments of the firm-specific distributions. The fact that skewness and kurtosis seem to be relevant predictors for future returns raises the question whether these higher moments can be predicted. Sun & Yan (2003) argue that skewness persistence is important, and helps investors exploit the skewness in portfolio formation. Only if skewness persists can investors use the ex-post knowledge about past skewness to proxy ex-ante skewness. Several empirical studies show that skewness is much more persistent for individual stocks than it is for portfolios (Simkowitz & Beedles, 1978; Singleton & Wingender, 1986; Lau et al., 1989; Muralidhar, 1993; DeFusco et al., 1996).

Risk-neutral higher moments seem to be related to stock returns. For skewness, Xing et al. (2010) and Stilger et al. (2017) document a positive relation, while Conrad et al. (2013) find a negative impact of option-implied skewness on future stock returns. Bali & Murray (2013) find a negative impact of option-implied skewness on future option returns. Borochin et al. (2018) document the differential pricing of short-term and long-term option-implied skewness in the cross-section of stock returns. For kurtosis, Conrad et al. (2013) report that risk-neutral kurtosis and stock returns are positively related. Amaya et al. (2015) investigate the asset pricing implications of realized moments and show that realized skewness is negatively priced while realized kurtosis does not seem to be priced. As opposed to these studies, we do not examine the effect of the level of higher moments but test whether the joint persistence of the option-implied central moments affects future asset returns.

The remainder of this paper is organized as follows. Section II describes our data set and the estimation methodology. In Section III, we test whether the joint persistence of the option implied distribution's central moments is priced in the cross-section of stock returns. Section IV analyzes the persistence of individual moments. Section V presents various additional analyses and robustness tests. Section VI concludes.

II Data and Methodology

A Data

We obtain daily stock returns, prices, as well as shares outstanding on companies traded at the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) from the Center for Research in Security Prices (CRSP). We exclude closed-end funds and REITs (SIC codes 6720–6730 and 6798). Balance sheet and income statement data come from Compustat. Options data are from the IvyDB OptionMetrics Volatility Surface, which provides implied volatilities for standardized delta levels and maturities. For our main analysis, we use the 365-day Volatility Surface file. To generate the Volatility Surface File, IvyDB uses a kernel smoothing algorithm that generates standardized options only *"if there exists enough option price data on that date to accurately interpolate the required values"*. For more details we refer the reader to the IvyDB technical document. We drop observations with missing option-implied volatilities. Finally, we drop stock–day observations where the call (put) option prices are not monotonically decreasing (increasing) with moneyness.

Our sample period ranges from January 01, 1996 to December 31, 2016. We only include stocks for which data from both CRSP and OptionMetrics are available. To avoid relying on illiquid options with stale underlying prices, we exclude very illiquid stocks. To be more precise, we expunge firm–month observations with prices below 10 U.S. dollars or a market capitalization below 400 million U.S. dollars (Bremer & Sweeney, 1991; Baltussen et al., 2018). As detailed in Table A1 of the Online Appendix, on average our final sample includes 1,807 stocks per month, which cover on average 87% of the market capitalization of the CRSP universe. These numbers are overall increasing over time, starting with 1,329 stocks in December 1996, which cover 80% of the CRSP market capitalization while reaching 2,379 stocks in December 2016, which cover in total 92% of the CRSP market capitalization.

We obtain data on the Fama & French (1993, 2015) as well as the momentum factors from Kenneth R. French's data library.[2] Data on the Pástor & Stambaugh (2003) liquidity factor come from the website of Lubos Pástor.[3]

B Methodology

Jondeau & Rockinger (2006) show that an investor's utility can be approximated by a Taylor series expansion, so that utility is represented by the central moments of the distribution. In order to apply this utility function, one needs to approximate the expected utility by truncating the infinite expansion at a certain level $\bar{k}$. Previous studies truncate this Taylor expansion at various different levels. While, for the classical portfolio theory, Markowitz (1952) truncates at $\bar{k} = 2$ and, e.g., Levy (1969), Hanoch & Levy (1970), and Jurczenko & Maillet (2001) truncate at $\bar{k} = 3$, Ederington (1986), Berényi (2001), and Jondeau & Rockinger (2006) argue that the inclusion of skewness and kurtosis leads to a better approximation of the expected utility. Therefore, we study the first four moments, truncating the utility function after the fourth moment.[4]

We measure the joint predictability of the risk-neutral distribution's central moments: volatility, skewness, and kurtosis by their 1-day lags.[5]

In so doing, we rely on the option implied moments of Bakshi et al. (2003), of which we describe the computation in detail in Section A of the Appendix. For each stock i, we

[2]Website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[3]Website: http://faculty.chicagobooth.edu/lubos.pastor/research.

[4]In the Physics literature, there are papers that also consider super skewness (fifth moment) or the super flatness/kurtosis (sixth moment) (Frenkiel & Klebanoff, 1965; Garg & Warhaft, 1998; Lindgren et al., 2004). In general, though, it holds that the higher the kurtosis, the lower is the probability that even higher moments exist. Given that asset returns are typically characterized by a high kurtosis, it is not surprising that we are not aware of any paper in Finance that goes beyond the fourth moment.

[5]The first moment under the risk-neutral return distribution is known ex-ante, which is why we only concentrate on higher moments.

estimate the following vector autoregressive (VAR) model:

$$\begin{bmatrix} V_{i,t} \\ S_{i,t} \\ K_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{V,i} \\ \alpha_{S,i} \\ \alpha_{K,i} \end{bmatrix} + \underbrace{\begin{bmatrix} \beta_{V,V,i} & \beta_{V,S,i} & \beta_{V,K,i} \\ \beta_{S,V,i} & \beta_{S,S,i} & \beta_{S,K,i} \\ \beta_{K,V,i} & \beta_{K,S,i} & \beta_{K,K,i} \end{bmatrix}}_{B} \begin{bmatrix} V_{i,t-1} \\ S_{i,t-1} \\ K_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{V,i,t} \\ \epsilon_{S,i,t} \\ \epsilon_{K,i,t} \end{bmatrix}, \tag{1}$$

where $V_{i,t}$, $S_{i,t}$, and $K_{i,t}$ are the implied volatility, skewness, and kurtosis of stock i at time (day) t over the next twelve months (Kelly et al., 2015) and $\epsilon_{V,i,t}$, $\epsilon_{S,i,t}$, and $\epsilon_{K,i,t}$ denote the error terms.[6]

For some assets, the return distribution incurs frequent and unpredictable changes over time. Hence, these assets will show only little persistence in the central moments of their risk-neutral distribution. If the moments of tomorrow's distribution are jointly largely unpredictable by their lags, one might consider this asset as more risky. On the other hand, if the central moments are highly persistent and tomorrow's distribution is well predictable by today's moments, it is surrounded by only little uncertainty. Thus, as our main measure, we use the explanatory power of the VAR system, comparing the (likelihoods of the) estimated model with a constant model:[7]

$$LR^{*}_{VAR(1),i} = 2(\hat{L}_i - \hat{L}_{0,i}), \tag{2}$$

[6]One might wonder whether there are sufficient data on options for long maturities. We find that for the stocks considered in our sample, there are on average 8 strikes with positive bid price for calls and 7 for puts for times-to-maturity between half a year and a year and about 5 for each for times-to-maturity above one year. The shares of stocks with multiple strikes available are also substantial for both horizons. This data should be sufficient to accurately estimate and interpolate option-implied moments. Nevertheless, in Section V.E we also consider shorter horizons for the implied moments ranging from one month to twelve months, for which there are typically even more strikes with a positive bid price available, and find results that are very similar.

[7]Theoretically, any sophisticated model for the prediction of realized or implied moments can be applied here, including stock characteristics or macroeconomic variables. We decide to rely on a very intuitive model using the lagged moments which should be directly linked to the persistence and predictability of the moments.

where $\hat{L} = L(\hat{\theta})$ is the log-likelihood of the model in Equation (1) and $\hat{L}_0 = L(\hat{\theta}_0)$ is the log-likelihood of the alternative constant model setting B equal to a matrix of zeros, and $\hat{\theta}$ and $\hat{\theta}_0$ are the maximum-likelihood estimates for the two models.

The moment persistence measure $LR^*_{VAR(1)}$ might be interpreted similarly to the R^2 in a simple linear regression: the more variation a model can explain, relative to a simple mean model benchmark, the better the predictability. In the case of Equation (2) a better predictability implies higher $LR^*_{VAR(1)}$ and, hence, higher persistence.

III Persistence and the Cross-Section of Stock Returns

We first present the parameter estimation results in Section III.A. Afterwards, we provide descriptive statistics for the moment persistence measure and examine whether firm characteristics are related to $LR_{VAR(1)}$ in Section III.B. Sections III.C and III.D investigate whether stocks with higher moment persistence generate different average returns compared to low-moment-persistence stocks. Finally, in Section III.E we directly test whether there is a return premium on moment persistence via cross-sectional regressions.

A Estimation Results

We estimate the system of Equation (1) for each stock separately. Since the persistence in a stock's distribution might change over time, and we are interested in the conditional relationship between moment persistence and expected returns, we allow for time-variation in the measure. More specifically, we re-estimate the VAR model at the end of each month using a rolling window, which includes the most recent year of daily observations on the implied moments.[8]

[8]For a stock to be included in our analysis, we require non-missing observations of the moments on at least 50% of the days of the estimation period.

Table 1 presents summary statistics on the estimation results, pooled for all stock–month observations. We find that the option-implied volatility is highly persistent on a day-by-day basis. The average $\beta_{V,V,i}$ coefficient is 0.87 and 90% of the parameter estimates lie between 0.45 and 1.01. Thus, overall volatility is highly persistent and seems well predictable by its own lags. On the contrary, lagged skewness and kurtosis, on average, seem to have less power for day-by-day volatility forecasts. The average of the coefficient $\beta_{V,S,i}$ is 0.04 and that of $\beta_{V,K,i}$ is 0.01, with distributions for both coefficients being closely centered around zero.

Option-implied skewness is less persistent than volatility. The average of the coefficient $\beta_{S,S,i}$, though, is still 0.57. Thus, risk-neutral skewness seems also relatively well predictable on a day-by-day basis. As is the case for volatility, there are few cross-moment linkages on average with lagged volatility and kurtosis. However, the distributions of these coefficients are substantially wider, implying strong cross-moment linkages for part of the stocks. For option-implied kurtosis, the average of the coefficient $\beta_{K,K,i}$ amounts to 0.50. Thus, also the risk-neutral kurtosis appears to be persistent. Interestingly, we find a sizable cross-moment linkage from past volatility to kurtosis. The average of the coefficient $\beta_{K,V,i}$ is –0.30. Hence, while all three central moments of the distribution are persistent, the cross-moment linkages are stronger in the higher moments, with volatility–kurtosis being the strongest link.[9]

B Summary Statistics

Having examined the estimation results for the coefficients of Equation (1), we next turn to the properties of $LR^*_{VAR(1)}$ as well as the main control variables used in this study.[10] Panel A of Table 2 reports summary statistics. The first row shows that the average of $LR^*_{VAR(1)}$ is 978, indicating that the VAR(1) model generally exhibits a substantially better in-sample

[9] One might intuitively expect the $\beta_{K,K,i}$ to be higher than $\beta_{S,S,i}$ since skewness is typically far more volatile than kurtosis. However, persistence, as measured by our VAR(1) model, is *not* the opposite of volatility. Empirically, we find that part of the "less-volatility" property of kurtosis is also reflected by the coefficient $\alpha_{K,i}$, for which the 5% and 95% quantiles are 0.27 and 3.36, respectively.

[10] Detailed descriptions of the control variables are available in Appendix B.

fit than the simple constant model. The 5% quantile of 389 supports this conjecture. The standard deviation of 352, along with the aforementioned quantiles of the distribution, indicate that there is substantial variation across assets in terms of the persistence of the central moments of their risk-neutral distributions. For our subsequent analyses, we standardize the measure $LR^*_{VAR(1)}$ to have zero mean and a volatility of 1 to ease the interpretability. We denote the standardized measure as $LR_{VAR(1)}$. Summary statistics for our main control variables are consistent with those in the relevant literature.

In a second step, we examine $LR_{VAR(1)}$ in relation to our main control variables. Panel B of Table 2 presents cross-sectional correlations of all variables for our sample period. We find that $LR_{VAR(1)}$ does not correlate strongly with any other variable. The market capitalization (Size), the bid–ask-spread (BAS), and volatility-of-volatility (Vol-of-vol) exhibit the highest absolute correlation coefficients with $LR_{VAR(1)}$, with values of 23%, −15%, and −24%, respectively. These correlations are consistent with the previous literature. Merton (1987), for example, argues that small and illiquid stocks exhibit incomplete information while Zhang (2006) argues that firm size is a proxy for information uncertainty, since small firms are less diversified and have less information available for the market than large firms. Higher information uncertainty makes the distribution more prone to large shocks. Similarly, the negative correlation with the volatility-of-volatility measure introduced by Baltussen et al. (2018) appears sensible, since the authors introduce volatility-of-volatility as a measure for uncertainty. That this correlation is relatively low is equally unsurprising, for several reasons. First, we examine the joint persistence of the central moments, i.e., volatility, skewness, and kurtosis, instead of only volatility. Second, and more importantly, persistence is *not* the antipode of volatility. One could think of numerous examples of volatile, but persistent, time-series or time-series with low volatility and also low persistence.[11]

C Portfolio Sorts

Having shown that moment persistence is largely unrelated to previously documented variables in the asset pricing literature, we next investigate whether investors demand compensation for holding assets with low persistence in their risk-neutral distribution's central moments by examining the relationship between moment persistence and future stock returns. Because stocks with more persistent central moments could be considered as less risky/uncertain, it is likely that investors require a premium to compensate them for holding low-moment-persistence stocks. Thus, we expect a negative price for moment persistence.

At the end of each month, we sort all stocks into quintile portfolios where the stocks with the lowest moment persistence are allocated to the first quintile and stocks with the highest moment persistence are assigned to the fifth quintile. In addition, we form a hedge portfolio (Q1–Q5) which buys the stocks in the portfolio with the lowest and simultaneously sells the stocks with the highest moment persistence. Excess returns of the equally and value-weighted portfolios are tracked over the subsequent month. Our analysis is out-of-sample in the sense that there is no overlap between the data used to estimate the VAR system and the data used to compute the excess returns of the portfolios. We regress the portfolio returns on risk factors in order to test whether these returns observed merely reflect passive exposure to standard factors. We include the market portfolio of the Capital Asset Pricing

[11] To see this point more clearly, consider a simple example (ignoring skewness and kurtosis for illustrative purposes): say, the option-implied central moments are constant over the whole period. This will lead to a volatility-of-volatility of zero. On the other hand, the moments are also perfectly predictable when using a VAR(1) model; but the entire predictability will be captured by the intercept term. Thus, the measure for moment persistence is equal to zero, too. Now, consider another extreme example. Say that the volatility is steadily increasing during a certain time period. The volatility-of-volatility, which does not take into account the time-structure of this increase, will be very high. However, also the moment persistence is likely high because a steady increase is predictable in a VAR(1) setup. These are only two stylized examples, but we hope these help to clarify that high moment persistence does not need to correspond with low volatility-of-volatility and vice versa.

Model (CAPM), which controls for systematic risk. We further include the size and value effects using the Fama & French (1993) three-factor model (FF3). We extend the model by additionally including a momentum factor (Carhart, 1997) (four-factor) and a liquidity factor (Pástor & Stambaugh, 2003) (five-factor). Lastly, we employ the Fama & French (2015) five-factor model (FF5).[12] We use robust Newey & West (1987) standard errors with 5 lags to assess the statistical significance.

Table 3 presents the results. In the first row, we report the average returns of all portfolios. The alphas of the different models are reported below. We find that average annualized returns follow a strictly decreasing pattern from 10.09% to 5.51% for equally weighted portfolios. The difference of 4.58% between the low-moment-persistence quintile and the high-moment-persistence quintile is statistically significant at the 5% level. For value-weighted returns, we obtain a largely similar pattern. While the quintile portfolios are not completely monotonically decreasing from Q1 to Q5, the annualized hedge portfolio return amounts to 4.38%. When controlling for the standard risk factor models, we obtain alphas for the hedge portfolio that are of similar magnitude as the Q1–Q5 excess returns. For value-weighted portfolios, the alphas amount to 5.29%, 4.25%, 3.65%, 3.47%, and 3.06%, for the CAPM, the FF3 model, the four-factor model, the five-factor model, and the FF5 model, respectively. All alphas are highly statistically significant. For equally weighted portfolios, the hedge portfolio alphas are typically even somewhat larger and similarly statistically significant. Passive exposure to these risk factors thus cannot explain the premium on moment persistence.

Having analyzed the portfolio sorts, two important questions remain. The first question is whether these results are "sufficiently significant". Harvey et al. (2016) caution that data snooping and publication bias can severely affect the external validity of empirical find-

[12] We also consider the Hou et al. (2015) q-factor model (HXZ), which leads to qualitatively similar results as the Fama & French (2015) five-factor model. Data on the factors were kindly provided by the authors.

ings. The authors suggest to use a critical value of 3.0 instead of 2.0 when assessing the statistical significance of an anomaly variable. The t-statistics of the portfolio sorts on moment persistence only partially clear this hurdle. For example for the CAPM Q1–Q5 alpha, the t-statistic (not tabulated) amounts to 3.89 (2.81) for equally weighted (value-weighted) portfolios. For FF5 alphas, these amount to 2.93 (2.08). We caution though that a sample period of effectively 20 years may not yield sufficient power to consistently deliver such high t-statistics. Nevertheless, one might be well advised to interpret our results cautiously in light of Harvey et al. (2016) and Hou et al. (2018). The second open question relates to the "exploitability" of the premium on moment persistence. Since we use a 12-month window to estimate the moment persistence, the estimates are quite persistent. Of the stocks allocated to Q1 in month $t-1$, 78% are also in Q1 in the next month. For Q5, the share of stocks still in the same portfolio after one month is 81%. After 6 months, still roughly 50% of the stocks that have been in these portfolios remain there. Thus, direct transaction costs for rebalancing the portfolios are modest. More importantly, when considering value-weighted returns, all alphas of the Q1 portfolio are significantly positive. Thus, to exploit the premium on moment persistence, one might simply buy the stocks in Q1, entirely sidestepping the problems posed by costly short selling.

D Double-Sorted Portfolios

For the univariate sorts in Section III.C, we find a both economically and statistically strong negative relationship between moment persistence and future stock returns, which cannot be explained by systematic risk factors. In this section, we test whether this relation persists when controlling for previously documented anomaly variables by performing double-sorts.

At the end of each month, we independently sort the stocks into quintile portfolios according to the control characteristic as well as moment persistence. We end up with a total of twenty-five portfolios. Using these twenty-five portfolios, we obtain the double-sorted quintile portfolios by averaging across the respective moment persistence quintiles within each of the quintiles sorted on one of the control characteristics. By doing so, we obtain quintile portfolios on moment persistence, which control for another characteristic without assuming any parametric form for the potential relationships.

We start by analyzing the full set of portfolios as well as the averages for the most obvious candidates for potentially related variables, that is, size, the bid–ask spread, idiosyncratic volatility, and volatility-of-volatility. In Table 4, we report the value-weighted Fama & French (2015) five-factor alphas for these double-sorts. Starting with size in Panel A, we find that the Q1–Q5 FF5 alpha is statistically significant within each of the first four size quintiles. The average Q1–Q5 FF5 alpha amounts to 5.58% with a t-statistic exceeding 3. Thus, size cannot explain the moment persistence premium we observe. On the contrary, for our sample, mostly consisting of large stocks, we do not find a negative premium for size in any of the five quintiles after controlling for moment persistence. The evidence can thus rather be interpreted such that persistence in the option-implied distribution's central moments might rationalize part of the size effect.

In Panel B of Table 4, we control for the bid–ask spread. We find that only for the Q5 bid–ask spread portfolio, there is a significant premium on moment persistence. However, the average premium for Q2 is of similar magnitude and only marginally insignificant (as are the Q1 and Q4 portfolios). Averaging across the five bid–ask spread portfolios, the Q1–Q5 alpha on moment persistence is highly statistically significant. Thus, overall, the bid–ask spread also cannot explain the premium we observe. In Panel C of Table 4, we present the results when controlling for idiosyncratic volatility. The results are similar as for the bid–ask spread. While the average FF5 alphas of portfolios Q2, Q3, Q4, and Q5 are economically large, only that of portfolio Q3 is statistically significant. Averaging across the quintiles, the moment persistence premium is statistically significant. Finally, Panel D of Table 4 presents the results when controlling for volatility-of-volatility. We find that the premium on moment persistence is high and statistically significant for the volatility-of-volatility quintiles Q4 and Q5. However, the point estimate for the FF5 alpha is also high for Q1. On average over the volatility-of-volatility quintiles, the premium on moment persistence remains highly statistically significant with a t-statistic exceeding 3.0.

In Table A2 of the Online Appendix, we repeat the analysis of Table 4 for equally weighted portfolios, finding qualitatively similar, though typically somewhat stronger, results. Thus, overall none of the four main control variables is able to explain the premium earned by stocks with less persistence in the option-implied central moments.

For further control variables, we proceed analogously, but only report the average double-sorted quintile portfolios to keep the presentation manageable. We present the equally and value-weighted Fama & French (2015) five-factor alphas for these in Table 5. We examine beta, book-to-market, momentum, short-term reversal, MAX, coskewness, and downside beta and find that none of these variables is able to explain the premium on moment persistence. The Q1–Q5 alphas for all these double-sorts are all of similar magnitude as those for the single-sorts and statistically significant. Thus, the negative return premium on moment persistence cannot be explained by any of these variables.

E Regression Tests

In a final step, we estimate Fama & MacBeth (1973) regressions in which we simultaneously control for different variables and test whether the degree of moment persistence contains information about future stock returns beyond that of various other firm characteristics. This analysis complements the uni- and bivariate portfolio sorts insofar as we directly estimate the cross-sectional premium on moment persistence. We use returns of individual stocks rather than stock portfolios, since for the latter the way the portfolios are formed can substantially affect the results and building portfolios typically leads to higher standard errors of the risk premium estimates (Lo & MacKinlay, 1990; Lewellen et al., 2010; Ang et al., 2018).

For each month, we regress the excess stock returns over the subsequent month on the stocks' moment persistence and stock characteristics all measured at the end of the current month:

$$r_{i,t+1} - r_{f,t+1} = \alpha_t + \gamma_t^C LR_{VAR(1),i,t} + \gamma_t^{Control} X_{i,t} + \epsilon_{i,t+1}, \tag{3}$$

where $r_{i,t+1}$ is the return of stock i over the next month and $r_{f,t+1}$ is the risk-free rate over the same period. To present our results, we annualize both $r_{i,t+1}$ and $r_{f,t+1}$. γ_t^C and $\gamma_t^{Control}$ are the premia associated with moment persistence and the remaining characteristics, respectively. $X_{i,t}$ is a vector containing one or more of the control variables and $\epsilon_{i,t+1}$ is the error term. In a second step, we perform tests on the time-series averages of the estimated monthly intercept and slope coefficients in order to test for the significance of the premia over the sample period. Again, we control for potential heteroskedasticity and autocorrelation by relying on Newey & West (1987) adjusted standard errors with 5 lags.[13]

The time-series averages of the coefficients $\hat{\alpha}_t$, $\hat{\gamma}_t^C$ and $\hat{\gamma}_t^{Control}$ are reported in Table 6. In column (I), we regress the stock excess returns on their moment persistence only. The market price of moment persistence is -1.33%. Thus, on average, a cross-sectional one-standard deviation decrease in our measure of moment persistence leads to an increase in annual excess returns of 1.33%. We find that controlling for further characteristics affects the cross-sectional risk premium on moment persistence only marginally and leaves the coefficient estimate strongly statistically significant. In models (XI) and (XII), the t-statistic for the

[13]For a better interpretability of the coefficients, we standardize all control variables as we do for $LR^*_{VAR(1)}$.

moment persistence premium even exceeds the rigorous threshold of 3 as recommended by Harvey et al. (2016).

The signs of the risk premia we find for the control variables are largely consistent with the previous literature. However, consistent with Hou et al. (2018), only few of these are statistically significant for our sample of large stocks. We find an insignificant negative size premium (Fama & French, 1993). The premium for value and the bid–ask spread are also not statistically significant when including our measure of moment persistence. Focusing on model (XII), we find a statistically significant positive premium on momentum (Jegadeesh & Titman, 1993) and a significant negative premium on short-term reversal (Jegadeesh, 1990). Idiosyncratic volatility and MAX have negative point estimates for their risk premium estimates, but these are not statistically significant. These findings are consistent with previous studies which show that the idiosyncratic volatility puzzle is primarily driven by small stocks (Fu, 2009) and firms with very high shares of retail investor ownership (Han & Kumar, 2013), which are largely excluded from our sample of optionable stocks. Luo et al. (2017) further argue that the pricing of idiosyncratic risk differs for small and large stocks. While negative for small stocks, it can turn positive for large stocks. Finally, we detect a negative volatility-of-volatility premium which is consistent with Baltussen et al. (2018).[14]

So far, we control for stock characteristics in the cross-sectional regressions. In a next step we further include the option-implied moments to ensure that the explanatory power of moment persistence is not due to the level of these moments. Since the regressions are estimated at a monthly frequency and the implied moments are available at a daily frequency we consider both the end-of-the-month implied moments (IV_{end}, IS_{end}, IK_{end}) or the monthly average of the implied moments (IV_{mean}, IS_{mean}, IK_{mean}). The results are reported in Table 7. We find that including the levels of option-implied moments does not change our previous

[14] We also consider the realized volatility-of-realized-volatility or the unscaled version with qualitatively similar results.

results. Moment persistence is significantly negatively priced in the cross-section of stock returns. Interestingly, we find that option-implied skewness is positively priced in the cross-section, consistent with Xing et al. (2010) and Stilger et al. (2017).

IV The Persistence of Individual Moments

In Section III, we show that stocks with high joint moment persistence exhibit low future returns. A natural next question is whether we need all central moments of the option-implied return distribution or whether the persistence of one of the moments subsumes the information contained in that of the other moments. In this section, we thus analyze the persistence of each of the moments separately and test whether the single-moment persistence is priced in the cross-section of stock returns.

We investigate the individual moments by applying a similar methodology as in Section III. For each of the option-implied central moments of a stock i we set up the following (independent) autoregressive models:

$$V_{i,t} = \alpha_{V,i} + \beta_{V,i} V_{i,t-1} + \epsilon_{V,i,t}, \tag{4}$$

$$S_{i,t} = \alpha_{S,i} + \beta_{S,i} S_{i,t-1} + \epsilon_{S,i,t}, \tag{5}$$

$$K_{i,t} = \alpha_{K,i} + \beta_{K,i} K_{i,t-1} + \epsilon_{K,i,t}, \tag{6}$$

and measure the persistence of the individual risk-neutral moments with the following likelihood ratios:

$$LR^*_{Vol,i} = 2(\hat{L}_{V,i} - \hat{L}_{V,0,i}), \tag{7}$$

$$LR^*_{Skew,i} = 2(\hat{L}_{S,i} - \hat{L}_{S,0,i}), \tag{8}$$

$$LR^*_{Kurt,i} = 2(\hat{L}_{K,i} - \hat{L}_{K,0,i}). \tag{9}$$

$\hat{L}_{V,i}$, $\hat{L}_{S,i}$, and $\hat{L}_{K,i}$ are the maximum log-likelihoods from Equations (4)–(6) while $\hat{L}_{V,0,i}$, $\hat{L}_{S,0,i}$, and $\hat{L}_{K,0,i}$ are the maximum log-likelihoods from the constant models setting the respective slope coefficients to zero.[15]

Panel A of Table 8 presents summary statistics for the persistence of individual moments. For all moments, the estimates of the likelihood ratio test are high on average, indicating that each of the single moments is persistent. The most persistent moment on average is the volatility, where the average LR^*_{Vol} amounts to 607. For LR^*_{Skew} and LR^*_{Kurt}, the averages are substantially lower, with 193 and 195, respectively. Overall, each LR^*_{Vol}, LR^*_{Skew}, and LR^*_{Kurt} are substantially smaller than $LR_{VAR(1)}$, indicating that using a model which allows for cross-moment linkages and examines the persistence of the option-implied central moment jointly delivers a substantially better fit to the data on average.

In Panel B of Table 8, we present correlations among the different persistence measures. We find that $LR_{VAR(1)}$ is strongly correlated with each LR_{Vol}, LR_{Skew}, and LR_{Kurt}. For LR_{Vol}, the correlation with $LR_{VAR(1)}$ amounts to 0.86 while for LR_{Skew} and LR_{Kurt}, the correlation is somewhat lower, with 0.66 and 0.67, respectively. Thus, much, but not all of the information contained in $LR_{VAR(1)}$ can be reproduced by the persistence of the individual moments.

Finally, Table 9 reports the results for equally and value-weighted portfolio sorts on LR_{Vol}, LR_{Skew}, and LR_{Kurt}. While each of the three moment persistence variables creates a positive spread return and FF5 alpha for the Q1–Q5 portfolio, none of the measures yields consistent statistically significant results. Thus, overall our results indicate that the joint persistence whole distribution is relevant. Examining one of the individual moments separately is not sufficient.

[15]As before, LR_{Vol}, etc. without star denotes the standardized measure, where we subtract LR^*_{Vol} of its mean and divide the result by the measure's standard deviation.

V Additional Analyses and Robustness Checks

A Less Frequent Rebalancing

To further examine whether the premium on moment persistence can be exploited in practice, we examine annual instead of monthly rebalancing strategies. That is, at the end of each January, we form the portfolios by sorting on moment persistence.[16] We then hold and track the non-rebalanced, non-overlapping one-month returns of these portfolios over the next twelve months. Thus, the inference is still based on 1-month returns without any overlap in observations.

We present these results in Table A3 of the Online Appendix. The results obtained are qualitatively similar as for monthly rebalancing of the portfolios. The Q1–Q5 portfolio yields statistically significant positive returns and alphas for all factor models. These are typically somewhat smaller in magnitude, though, pointing toward a benefit of using more timely information as is inherent in more frequent rebalancing.

B Further Control Variables

In this section, we test whether further control variables can explain the premium we observe for stocks whose central moments of the risk-neutral distribution are less persistent. One might argue that higher persistence can be associated with fewer occurrences of jumps in returns. Thus, we follow Pukthuanthong & Roll (2015) and control for jumps using the Barndorff-Nielsen & Shephard (2006) (BNS) jump test statistic.[17] Furthermore, we control for firm age (Zhang, 2006), dispersion in analyst forecasts (Anderson et al., 2009), as well as the stock variance risk premium (Bali & Hovakimian, 2009). Lastly, we also include

[16] The results are qualitatively similar when choosing other months as dates for rebalancing.

[17] Pukthuanthong & Roll (2015) show in simulations, using different jump sizes and frequencies, that this test is preferable to those proposed by Lee & Mykland (2008), Jiang & Oomen (2008), and Jacod & Todorov (2009).

expected idiosyncratic skewness (Boyer et al., 2009). This measure may also be related to the persistence of higher moments.

Table A4 of the Online Appendix reports the FF5 alphas for double-sorted portfolios on moment persistence and the control variables. We find that none of these variables can explain the premium on moment persistence.

To further test the robustness of our results, we also include these variables in Fama & MacBeth (1973) regressions in Table A5 of the Online Appendix, finding that none of the additional variables affects the point estimate or the statistical significance of the cross-sectional risk premium on moment persistence.

C Implied vs. Realized Moments

We measure moment persistence as the persistence of the option-implied higher moments (volatility, skewness, and kurtosis). There is an ongoing debate in the literature related to implied vs. realized moments regarding their predictive power and importance for portfolio allocation. Several papers emphasize the usefulness of the option-implied distribution. For example, Chang et al. (2012) find that the predictive power of option-implied betas is stronger for both the cross-section and future betas compared to historical betas. Their proposed option-implied beta is calculated from option-implied estimates of variance and skewness. Kostakis et al. (2011) argue that the use of (risk-adjusted) implied distributions leads to a better portfolio allocation of investors compared to the use of historical return distribution. DeMiguel et al. (2013) show that the use of option-implied moments (volatility and skewness) leads to an improved (optimal) portfolio allocation in terms of Sharpe ratios.

We complement these studies and provide empirical evidence on the predictive power of implied moments as opposed to realized moments. For each stock i we estimate the following two predictive regressions:

$$RMoment_{i,t} = a_i + b_i IMoment_{i,t-1} + \epsilon_{i,t}, \tag{10}$$

$$RMoment_{i,t} = a_i + b_i RMoment_{i,t-1} + \epsilon_{i,t}, \tag{11}$$

where $RMoment_{i,t}$ is the realized moment (volatility, skewness or kurtosis) while $IMoment_{i,t}$ is the option-implied moment (volatility, skewness or kurtosis) at time t. We calculate realized moments following Amaya et al. (2015), relying on monthly estimates using daily returns rather than daily moments from high-frequency returns. The monthly volatility, skewness, and kurtosis RV_t, RS_t, RK_t are calculated as follows:

$$RV_t = \sum_{i=1}^{N} r_{t,i}^2, \tag{12}$$

$$RS_t = \frac{\sqrt{N}\sum_{i=1}^{N} r_{t,i}^3}{RV_t^{3/2}}, \tag{13}$$

$$RK_t = \frac{N\sum_{i=1}^{N} r_{t,i}^4}{RV_t^2}, \tag{14}$$

where $r_{t,i}$ is the ith return in month t and typically $i = 1, ..., N = 22$.

The results are reported in Table A6 of the Online Appendix. We find that the explanatory power in terms of average adjusted R^2s is significantly higher for all moments when relying on implied moments as predictors rather than their past realized counterparts.

D Alternative Holding Period

In our main analysis we hold the stocks for one month, while showing that a 12-month non-overlapping window also creates a significant premium on moment persistence. In this section, we complement these analyses by examining a 3-month overlapping holding period. We present the portfolio sorts in Table A7 of the Online Appendix and the Fama & MacBeth

(1973) regression results in Tables A8 and A9 of the Online Appendix. Overall, the results are qualitatively similar as for the 1-month holding period.

E Alternative Option Horizons

In our main analysis, we rely on an option horizon of twelve months. However, typically shorter-term options are considered more liquid than long-term options. Thus, in this section, we examine the robustness of our main results to using one-month (30-day), three-month (91-day), and six-month (182-day) horizons in addition to our main horizon.[18]

Table A10 of the Online Appendix presents summary statistics for the moment persistence measures based on different implied horizons. We find that the value of the measures is generally high, but increasing with the option horizon. Thus, as one might intuitively expect, the central moments of the 365-day option-implied distribution are considerably more persistent on average than those for the 30-day option-implied distribution. The correlations between the measures increase the larger the differences in the option horizons.

In Table A11 of the Online Appendix, we present the portfolio results for the least persistent 30-day horizon. The results are qualitatively similar to and only slightly weaker than for our main measure based on 365-day options.

Table A12 of the Online Appendix further presents the regressions results for all alternative option-implied horizons. We find that, independent of the horizon, all moment persistence measures yield a significant negative cross-sectional price of risk.

[18]For the one-month horizon, there are generally less data available than for longer horizons. Additionally, the OptionMetrics kernel smoothing algorithm sometimes creates observations for the standardized options that do not comply with standard (monotonicity) no-arbitrage requirements. If the options for a stock violate these no-arbitrage rules, we set the moment observations as not available.

F Alternative Model Specification

Finally, we examine the robustness of our results to using alternative specifications of the vector autoregressive system. That is, we also consider alternative $VAR(p)$ specifications including a higher number of lags. We include the previous week ($p = 5$) or the previous month ($p = 22$) as well as a heterogeneous specification: in the spirit of Corsi (2009) we estimate a heterogeneous vector-autoregressive (HVAR) model, see for example Bollerslev & Todorov (2011), relying on three explanatory variables per equation of the system: the previous day's moments, the previous week's moments calculated as the weekly averages, and the previous month's moments calculated as the monthly averages:

$$\boldsymbol{M}_t = \boldsymbol{A_0} + \boldsymbol{A_1}\boldsymbol{M_{t-1}} + \boldsymbol{A_2}\sum_{i=1}^{5}\boldsymbol{M_{t-i}}/5 + \boldsymbol{A_3}\sum_{i=1}^{22}\boldsymbol{M_{t-i}}/22 + \boldsymbol{\epsilon_t}, \tag{15}$$

for the three-dimensional vector

$$\boldsymbol{M_t} \equiv (V_t, S_t, K_t)'. \tag{16}$$

$\boldsymbol{A_0}$ is a 3x1 parameter vector and $\boldsymbol{A_1}$, $\boldsymbol{A_2}$, and $\boldsymbol{A_3}$ are 3x3 parameter matrices.

Table A13 of the Online Appendix presents the summary statistics for these alternative measures. We find that $LR_{VAR(5)}$ and $LR_{VAR(22)}$ are on average slightly higher than $LR_{VAR(1)}$, indicating a better in-sample fit to the data when including more lags. However, the increase is modest and we are less interested in the in-sample fit of the model than in its out-of-sample predictability for future returns in the cross-section. For $LR_{HVAR(3)}$, the fit is on average worse than for $LR_{VAR(1)}$.

Table A14 of the Online Appendix presents the results for the portfolio sorts on $LR_{VAR(5)}$. These are qualitatively similar as for $LR_{VAR(1)}$.

Finally, in Table A15 of the Online Appendix, we present the regression results for all alternative model specifications. Overall, the results are qualitatively similar for these alternative models as for $LR_{VAR(1)}$. However, the better in-sample explanatory power when using more lags does not translate to enhanced out-of-sample return predictability. For all alternative models, the cross-sectional risk premium is smaller and its statistical significance is weaker than for $LR_{VAR(1)}$. For $LR_{VAR(22)}$, the univariate cross-sectional risk premium estimate even turns insignificant.

VI Conclusion

In this paper, we examine the asset pricing implications of the joint persistence of the option-implied central moments of the risk-neutral return distribution. We find that stocks with higher moment persistence yield substantially lower average returns than stocks with lower moment persistence. When buying the quintile of stocks with the lowest and at the same time selling the quintile of stocks with the highest persistence of the option-implied central moments, one earns value-weighted annual returns and five-factor alphas of 4.38% and 3.06%, respectively. These results cannot be explained by previously documented risk factors and return anomalies.

Thus, there is a strongly negative moment persistence premium in the cross-section of U.S. stock returns. Investors appear to demand a high premium for keeping "devils" they *do not know.*

Appendix

A Model-Free Option-Implied Moments

We compute the model-free option-implied volatility, skewness, and kurtosis following Bakshi et al. (2003), who make use of the property that any payoff can be spanned using a continuum of out-of-the-money (OTM) puts and calls (Bakshi & Madan, 2000), as well as Jiang & Tian (2005). To do so, we follow Chang et al. (2012), and first compute ex-dividend stock prices. Next, we interpolate implied volatilities on a grid of 1,000 moneyness levels (K/S, strike-to-spot), equally spaced between 0.3% and 300%, for any given stock and trading day. We extrapolate implied volatilities outside the range of available strike prices using the value for the smallest, respectively largest, available moneyness level (as in Jiang & Tian, 2005 and Chang et al., 2012). We use the interpolated volatilities to compute Black & Scholes (1973) option prices for calls, $C(\cdot)$, if K/S>1 and puts, $P(\cdot)$, if K/S<1. We use these prices to obtain the prices of the volatility (QUAD), the CUBIC, and the quartic (QUART) contract:

$$\begin{aligned}
\text{QUAD} &= \int_S^\infty \frac{2\left(1-\ln\left[\frac{K}{S}\right]\right)}{K^2} C(T-t,K)dK \\
&+ \int_0^S \frac{2\left(1+\ln\left[\frac{S}{K}\right]\right)}{K^2} P(T-t,K)dK, \qquad \text{(A1)}\\
\text{CUBIC} &= \int_S^\infty \frac{6\ln\left[\frac{K}{S}\right]-3\left(\ln\left[\frac{K}{S}\right]\right)^2}{K^2} C(T-t,K)dK \\
&+ \int_0^S \frac{6\ln\left[\frac{S}{K}\right]+3\left(\ln\left[\frac{S}{K}\right]\right)^2}{K^2} P(T-t,K)dK, \qquad \text{(A2)}\\
\text{QUART} &= \int_S^\infty \frac{12\left(\ln\left[\frac{K}{S}\right]\right)^2-4\left(\ln\left[\frac{K}{S}\right]\right)^3}{K^2} C(T-t,K)dK \\
&+ \int_0^S \frac{12\left(\ln\left[\frac{S}{K}\right]\right)^2+4\left(\ln\left[\frac{S}{K}\right]\right)^3}{K^2} P(T-t,K)dK. \qquad \text{(A3)}
\end{aligned}$$

We approximate the integrals using a trapezoidal rule (Dennis & Mayhew, 2002). The option-implied moments can be computed as:

$$V_t^2 = \frac{e^{r_{f,t}(T-t)}\text{QUAD} - \mu_t^2}{T-t}, \tag{A4}$$

$$S_t = \frac{e^{r_{f,t}(T-t)}\text{CUBIC} - 3\mu_t e^{r_{f,t}(T-t)}\text{QUAD} + 2\mu_t^3}{[e^{r_{f,t}(T-t)}\text{QUAD} - \mu_t^2]^{3/2}}, \tag{A5}$$

$$K_t = \frac{e^{r_{f,t}(T-t)}\text{QUART} - 4\mu_t e^{r_{f,t}(T-t)}\text{CUBIC} + 6\mu_t^2 e^{r_{f,t}(T-t)}\text{QUAD} - 3\mu_t^4}{[e^{r_{f,t}(T-t)}\text{QUAD} - \mu_t^2]^2}, \tag{A6}$$

$$\mu_t = e^{r_{f,t}(T-t)} - 1 - \frac{e^{r_{f,t}(T-t)}}{2}\text{QUAD} - \frac{e^{r_{f,t}(T-t)}}{6}\text{CUBIC} - \frac{e^{r_{f,t}(T-t)}}{24}\text{QUART}, \tag{A7}$$

where $r_{f,t}$ denotes the risk-free rate and $T-t$ the time to maturity of the contract. V_t^2 is the annualized option-implied variance and S_t and K_t are the option-implied skewness and kurtosis, respectively.

B Control Variables

- **Age** (Zhang, 2006) is the number of years up to time t since a firm first appeared in the CRSP database.

- **Beta** (Fama & MacBeth, 1973) is the slope coefficient from a market model regression using one year of daily returns. The regression equation is $r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta_{i,t}^M (r_{M,\tau} - r_{f,\tau}) + \epsilon_{i,\tau}$, where $r_{i,\tau}$ and $r_{M,\tau}$ are the return of stock j and the market (proxied by the CRSP value-weighted index) at day τ, respectively. $r_{f,\tau}$ is the risk-free rate at the same day. Beta is the coefficient $\beta_{i,t}^M$.

- **Bid–ask spread** (Amihud & Mendelson, 1986, "BAS") is the stock's average daily relative bid–ask spread during the previous month.

- **Book-to-market** (Fama & French, 1992) is the most current observation for book equity divided by the end-of-year market capitalization of the corresponding fiscal year. Following the standard in the literature, we assume that the book equity of the previous year's balance sheet statement becomes available at the end of June. Book equity is defined as stockholders' equity, plus balance sheet deferred taxes and investment tax credit, plus post-retirement benefit liabilities, minus the book value of preferred stock.

- **Coskewness** (Harvey & Siddique, 2000) and **Cokurtosis** (Dittmar, 2002) are the coefficients $\beta_{i,t}^{CS}$ and $\beta_{i,t}^{CK}$ in the regression $r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta_{i,t}^{M}(r_{M,\tau} - r_{f,\tau}) + \beta_{i,t}^{CS}(r_{M,\tau} - r_{f,\tau})^2 + \beta_{i,t}^{CK}(r_{M,\tau} - r_{f,\tau})^3 + \epsilon_{i,\tau}$, including the market excess return, the squared market excess return, and the cubed market excess return. The regression is estimated using daily returns over the previous year.

- **Downside beta** (Ang et al., 2006a, "DBeta") is the coefficient $\beta_{i,t}^{D}$ in the regression $r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta_{i,t}^{D}(r_{M,\tau} - r_{f,\tau}) + \epsilon_{i,\tau}$, using daily returns over the previous year only when the market return is below the average daily market return over that year.

- **Expected idiosyncratic skewness** (Boyer et al., 2009, "EIS") is estimated as the fitted expected value from the cross-sectional regression $iSkew_{i,t} = \beta_{0,t} + \beta_{1,t} iSkew_{i,t-1} + \beta_{2,t} iVol_{i,t-1} + \lambda_t X_{i,t-1} + \epsilon_{i,t}$. The regression is run for every month and the fitted values are obtained using the average of the coefficient estimates during the most recent 60 months. Each month, the regression uses monthly observations of idiosyncratic volatility and skewness and the control variables at time $t-1$. Idiosyncratic volatility is estimated as detailed below and idiosyncratic skewness is $\frac{1}{N}\sum_{\tau \in S(t)} \epsilon_{i,\tau} iVol_{i,t}^{-3}$, where the $\epsilon_{i,\tau}$ are the residuals from the Fama & French (1993) three-factor model. The vector of control variables $X_{i,t-1}$ includes momentum, turnover, size dummy variables (small vs. medium vs. large), industry dummy variables based on two-digit SIC codes, and a NASDAQ dummy variable.

- **Forecast dispersion** (Diether et al., 2002, "Dispersion") is the standard deviation of analysts' earnings forecasts for the current fiscal year divided by the absolute value of the mean earnings forecast. We obtain the data on the standard deviation and mean of earnings forecasts from the Unadjusted Summary History file of I/B/E/S.

- **Idiosyncratic volatility** (Ang et al., 2006b, "iVol") is the standard deviation of the residuals $\epsilon_{i,\tau}$ in the Fama & French (1993) three-factor model $r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} +$

$\beta^M_{i,t}(r_{M,\tau} - r_{f,\tau}) + \beta^S_{i,t} SMB_\tau + \beta^H_{i,t} HML_\tau + \epsilon_{i,\tau}$, using daily returns over the previous year. SMB_τ and HML_τ denote the returns on the Fama & French (1993) factors.

- **Jumps** (Pukthuanthong & Roll, 2015, "BNS") are measured with the Barndorff-Nielsen & Shephard (2006) G measure jump test statistic. To compute the test statistic, we use daily returns over the previous year.

- **Leverage** (Bhandari, 1988) is defined as one minus book equity (see "Book-to-market") divided by total assets (Compustat: AT). Book equity and total assets are updated every twelve months at the end of June.

- **Maximum return** (Bali et al., 2011, "MAX") is the average of the five highest daily returns during the previous year.

- **Momentum** (Jegadeesh & Titman, 1993) is the cumulative stock return over the period from $t-12$ until $t-1$. We exclude the preceding month's return to isolate momentum from short-term reversal.

- **Short-term reversal** (Jegadeesh, 1990) is the preceding month's stock return (from $t-1$ to t).

- **Size** (Banz, 1981) is the current market capitalization of a firm. Market capitalization is computed as the product of the stock price and the number of shares outstanding.

- **Variance risk premium** (Bollerslev et al., 2009, "VRP") is the difference between the implied and realized variance of stock i $VRP_{i,t} = IV^2_{i,t} - RV_{i,t}$, where $RV_{i,t}$ is the end-of-month realized variance and $IV_{i,t}$ is the implied volatility for stock i at the end of month t.

- **Vol-of-vol** (Baltussen et al., 2018) is the volatility of option-implied volatilities of a stock during the past month divided by the average of the option-implied volatility.

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Table 1: Estimation Results

This table presents summary statistics about each of the coefficients stacked in the matrix B of the VAR(1) model

$$\begin{bmatrix} V_{i,t} \\ S_{i,t} \\ K_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{V,i} \\ \alpha_{S,i} \\ \alpha_{K,i} \end{bmatrix} + \underbrace{\begin{bmatrix} \beta_{V,V,i} & \beta_{V,S,i} & \beta_{V,K,i} \\ \beta_{S,V,i} & \beta_{S,S,i} & \beta_{S,K,i} \\ \beta_{K,V,i} & \beta_{K,S,i} & \beta_{K,K,i} \end{bmatrix}}_{B} \begin{bmatrix} V_{i,t-1} \\ S_{i,t-1} \\ K_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{V,i,t} \\ \epsilon_{S,i,t} \\ \epsilon_{K,i,t} \end{bmatrix}.$$

We present the summary statistics of the point estimates for each of the coefficients separately. The summary statistics are ordered according to those in the B-matrix. The first subscript of the coefficients denotes the regressand *(name in row)* while the second subscript indicates the regressor *(name in column)*. For example, the coefficient $\beta_{K,V,i}$ measures the sensitivity of the Kurtosis to the one-day lagged volatility and is placed in the row denoted by 'Kurt' and the column indicated by 'Vol'. To limit the effect of outliers, we winsorize the distribution of each coefficient at the 1% and 99% levels. Mean is the overall average of the coefficients. Std. is the standard deviation. 5%, Median, and 95% indicate the corresponding quantiles, respectively.

	Vol					Skew					Kurt				
	Mean	Std.	5%	Median	95%	Mean	Std.	5%	Median	95%	Mean	Std.	5%	Median	95%
Vol	0.87	0.18	0.45	0.94	1.02	0.04	0.05	-0.02	0.02	0.13	0.01	0.03	-0.04	0.00	0.07
Skew	0.07	0.76	-1.00	0.04	1.29	0.57	0.27	0.11	0.60	0.94	-0.09	0.16	-0.38	-0.07	0.13
Kurt	-0.30	1.22	-1.94	-0.23	1.17	0.06	0.63	-0.35	-0.05	0.70	0.50	0.28	0.03	0.52	0.90

Table 2: Summary Statistics and Cross-Sectional Correlations

This table presents summary statistics for (Panel A) and correlations among (Panel B) our main variables. Mean is the time-series average of the cross-sectional average. Std., Skewness, and Kurtosis present the average cross-sectional standard deviation, skewness, and kurtosis, respectively. Min and Max report the time-series average of the minimum and maximum observation in the cross-section. 5%, 25%, Median, 75% and 95% indicate the averages of the corresponding cross-sectional quantiles. $LR^*_{VAR(1)}$ denotes the raw (non-standardized) $LR_{VAR(1)}$ measure. Panel B presents the average cross-sectional correlations of the main variables. The sample period is January 1996 until December 2016.

Panel A: Summary Statistics:

	Mean	Std.	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
$LR^*_{VAR(1)}$	978	352	0.00	2.46	3.13	389	740	984	1,209	1,561	2,200
$LR_{VAR(1)}$	0.00	1.00	0.00	2.46	-2.88	-1.69	-0.67	0.02	0.66	1.64	3.48
Beta	0.99	0.62	0.11	2.77	-3.30	0.16	0.63	0.94	1.31	2.03	4.09
Size	3.84	15.6	0.79	3.85	0.00	0.03	0.18	0.60	2.07	15.1	406
Book-to-market	3.48	104	0.60	3.63	-58.3	0.06	0.28	0.52	0.88	2.69	5,955
BAS	0.01	0.01	1.86	8.45	-0.00	0.00	0.00	0.01	0.01	0.03	0.34
Momentum	0.15	0.67	0.96	5.45	-0.97	-0.53	-0.17	0.06	0.31	1.08	15.2
Short-term reversal	0.01	0.15	0.61	7.09	-0.84	-0.19	-0.06	0.00	0.07	0.24	2.40
Leverage	0.54	0.52	0.20	2.49	-0.01	0.11	0.31	0.51	0.72	0.95	19.5
iVol	0.02	0.02	1.96	10.3	0.00	0.01	0.01	0.02	0.03	0.06	0.43
Max	0.10	0.08	0.81	3.54	0.01	0.03	0.06	0.09	0.13	0.24	1.46
Coskewness	-2.59	16.8	-0.19	4.96	-162	-29.1	-9.75	-1.76	5.35	20.6	171
Cokurtosis	-74.7	1,050	-0.08	7.36	-11,098	-1,629	-536	-49.4	393	1,409	11,838
DBeta	1.02	0.73	0.09	3.13	-5.39	0.06	0.62	0.96	1.39	2.23	5.98
Vol-of-Vol	0.05	0.05	2.03	9.67	0.00	0.01	0.02	0.03	0.05	0.12	0.70

Panel B: Cross-sectional Correlations:

	$LR_{VAR(1)}$	Beta	Size	Book-to-market	BAS	Momentum	ST Reversal	Leverage	iVol	Max	Coskewness	Cokurtosis	DBeta	Vol-of-vol
$LR_{VAR(1)}$	∗	0.11	0.23	0.02	−0.15	−0.04	−0.03	0.05	−0.01	−0.02	0.01	0.02	0.10	−0.21
Beta		∗	0.02	0.01	−0.20	0.02	−0.02	−0.04	0.14	0.20	0.09	−0.04	0.80	−0.04
Size			∗	−0.01	−0.10	0.03	0.01	0.04	−0.12	−0.13	0.04	0.03	−0.00	−0.07
Book-to-market				∗	0.04	0.00	0.00	0.02	−0.00	−0.01	0.00	0.02	0.01	0.01
BAS					∗	−0.16	−0.03	0.01	0.43	0.43	−0.08	0.04	−0.12	0.14
Momentum						∗	0.03	0.04	−0.10	0.04	−0.04	0.03	0.04	−0.03
Short-term reversal							∗	0.01	0.12	0.05	0.00	0.01	−0.01	0.01
Leverage								∗	−0.05	−0.02	0.01	0.02	−0.02	0.02
iVol									∗	0.67	−0.11	−0.02	0.17	0.14
Max										∗	−0.11	−0.01	0.24	0.06
Coskewness											∗	0.10	−0.34	−0.02
Co Kurtosis												∗	0.12	0.02
DBeta													∗	−0.02
Vol-of-Vol														∗

Table 3: Portfolio Sorts

At the end of each month, we sort the stocks into five portfolios according to their $LR_{VAR(1)}$. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1)}$. Panel A presents the results for equally weighted portfolio sorts while in Panel B we weigh the stocks in each portfolio according to their market value. We hold the portfolios for one month. The row labeled Average Return return denotes the average portfolio excess return. CAPM alpha, FF3 alpha, four-factor alpha, five-factor alpha, and FF5 alpha refer to the alphas of the CAPM, the Fama & French (1993) three-factor the Carhart (1997) four-factor model, the five-factor model (including Pástor & Stambaugh, 2003 liquidity), and the Fama & French (2015) five-factor model, respectively. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Average Return	0.1009**	0.0880**	0.0835*	0.0708	0.0551	0.0458**
	(0.0420)	(0.0427)	(0.0435)	(0.0464)	(0.0501)	(0.0178)
CAPM alpha	0.0295*	0.0139	0.0069	−0.0092	−0.0303**	0.0598***
	(0.0177)	(0.0157)	(0.0158)	(0.0158)	(0.0145)	(0.0154)
FF3 alpha	0.0160*	0.0033	−0.0038	−0.0180	−0.0373***	0.0533***
	(0.0096)	(0.0090)	(0.0108)	(0.0135)	(0.0121)	(0.0126)
four-factor alpha	0.0138	0.0058	0.0024	−0.0087	−0.0256**	0.0394***
	(0.0107)	(0.0089)	(0.0103)	(0.0123)	(0.0111)	(0.0123)
five-factor alpha	0.0106	0.0002	−0.0029	−0.0146	−0.0288***	0.0394***
	(0.0105)	(0.0085)	(0.0104)	(0.0118)	(0.0110)	(0.0123)
FF5 alpha	0.0114	−0.0010	−0.0084	−0.0218*	−0.0290**	0.0404***
	(0.0103)	(0.0084)	(0.0098)	(0.0127)	(0.0123)	(0.0138)
Panel B: Value-Weighted:						
Average Return	0.1050***	0.0844**	0.0583	0.0652	0.0612	0.0438**
	(0.0344)	(0.0360)	(0.0377)	(0.0412)	(0.0436)	(0.0197)
CAPM alpha	0.0430***	0.0195*	−0.0086	−0.0028	−0.0099	0.0529***
	(0.0123)	(0.0114)	(0.0088)	(0.0092)	(0.0105)	(0.0188)
FF3 alpha	0.0354***	0.0193*	−0.0095	−0.0029	−0.0071	0.0425***
	(0.0097)	(0.0116)	(0.0078)	(0.0091)	(0.0097)	(0.0150)
four-factor alpha	0.0291***	0.0197*	−0.0099	−0.0034	−0.0074	0.0365**
	(0.0101)	(0.0115)	(0.0080)	(0.0094)	(0.0098)	(0.0156)
five-factor alpha	0.0268***	0.0141	−0.0134*	−0.0079	−0.0080	0.0347**
	(0.0102)	(0.0109)	(0.0079)	(0.0095)	(0.0101)	(0.0161)
FF5 alpha	0.0260**	0.0120	−0.0148*	−0.0084	−0.0045	0.0306**
	(0.0108)	(0.0129)	(0.0079)	(0.0095)	(0.0100)	(0.0147)

Table 4: Double-Sorted Portfolios

This table reports value-weighted Fama & French (2015) five-factor alphas for double-sorted portfolios. At the end of each month, we independently sort the stocks into five times five portfolios according to the characteristic denoted in the panel headings and their $LR_{VAR(1)}$. This results in a total of 25 portfolios. The row (column) labeled Q1–Q5 refers to the hedge portfolios for $LR_{VAR(1)}$ (the control variable). The column Avg. presents the average of the $LR_{VAR(1)}$ quintiles across the five quintiles of the control variable. We hold the portfolios for one month. We perform double sorts on size (Panel A), BAS (Panel B), iVol (Panel C), and Vol-of-Vol (Panel D). Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Size:

		Size						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0083	−0.0059	0.0262*	0.0225	0.0169	−0.0085	0.0136
		(0.0162)	(0.0137)	(0.0133)	(0.0152)	(0.0227)	(0.0287)	(0.0099)
	Q2	0.0096	−0.0208	−0.0062	0.0048	0.0148	−0.0052	0.0004
		(0.0147)	(0.0127)	(0.0132)	(0.0145)	(0.0179)	(0.0219)	(0.0094)
	Q3	−0.0243	−0.0198	−0.0119	0.0153	−0.0196*	−0.0047	−0.0121
		(0.0178)	(0.0153)	(0.0148)	(0.0159)	(0.0102)	(0.0206)	(0.0092)
	Q4	−0.0623**	−0.0172	−0.0427**	0.0023	−0.0058	−0.0566*	−0.0251*
		(0.0275)	(0.0199)	(0.0188)	(0.0150)	(0.0106)	(0.0299)	(0.0129)
	Q5	−0.0920***	−0.0690***	−0.0364	−0.0119	−0.0019	−0.0901***	−0.0422***
		(0.0252)	(0.0234)	(0.0227)	(0.0184)	(0.0107)	(0.0306)	(0.0133)
	Q1–Q5	0.1004***	0.0631**	0.0626**	0.0344*	0.0188		0.0558***
		(0.0305)	(0.0271)	(0.0243)	(0.0199)	(0.0260)		(0.0152)

Panel B: Bid–Ask Spread:

		BAS						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0627**	0.0848***	−0.0036	0.0013	−0.0230	0.0856**	0.0244**
		(0.0245)	(0.0307)	(0.0170)	(0.0171)	(0.0217)	(0.0334)	(0.0116)
	Q2	0.0165	0.0188	−0.0022	−0.0243	−0.0002	0.0166	0.0017
		(0.0264)	(0.0213)	(0.0195)	(0.0217)	(0.0205)	(0.0340)	(0.0124)
	Q3	0.0200	−0.0009	0.0117	−0.0630***	−0.0248	0.0449	−0.0114
		(0.0208)	(0.0192)	(0.0226)	(0.0224)	(0.0210)	(0.0342)	(0.0104)
	Q4	0.0507*	−0.0302	−0.0143	−0.0088	−0.0663**	0.1170***	−0.0138
		(0.0269)	(0.0187)	(0.0205)	(0.0242)	(0.0258)	(0.0407)	(0.0125)
	Q5	0.0249	0.0139	−0.0106	−0.0356	−0.0994***	0.1244***	−0.0214
		(0.0185)	(0.0300)	(0.0297)	(0.0316)	(0.0320)	(0.0435)	(0.0146)
	Q1–Q5	0.0378	0.0709	0.0070	0.0370	0.0765**		0.0458***
		(0.0243)	(0.0461)	(0.0357)	(0.0285)	(0.0346)		(0.0168)

Table 4: Double-Sorted Portfolios (continued)

Panel C: Idiosyncratic Volatility:

		iVol						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0187	0.0344**	0.0310*	0.0307	0.0138	0.0049	0.0257**
		(0.0177)	(0.0149)	(0.0181)	(0.0209)	(0.0209)	(0.0265)	(0.0107)
	Q2	0.0097	0.0312*	0.0083	0.0156	−0.0405	0.0502*	0.0049
		(0.0132)	(0.0183)	(0.0247)	(0.0275)	(0.0272)	(0.0296)	(0.0146)
	Q3	−0.0038	−0.0405***	−0.0310	0.0070	0.0435	−0.0472	−0.0050
		(0.0172)	(0.0154)	(0.0251)	(0.0204)	(0.0356)	(0.0399)	(0.0089)
	Q4	0.0095	−0.0224	−0.0133	−0.0102	−0.0234	0.0329	−0.0120
		(0.0123)	(0.0166)	(0.0206)	(0.0229)	(0.0271)	(0.0302)	(0.0114)
	Q5	0.0191	−0.0033	−0.0285	−0.0046	−0.0189	0.0379	−0.0072
		(0.0154)	(0.0161)	(0.0209)	(0.0245)	(0.0372)	(0.0419)	(0.0111)
	Q1–Q5	−0.0003	0.0376	0.0595**	0.0353	0.0327		0.0330**
		(0.0251)	(0.0234)	(0.0258)	(0.0273)	(0.0359)		(0.0133)

Panel D: Vol-of-Vol:

		Vol-of-vol						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0374	0.0109	0.0206	0.0258	0.0286	0.0088	0.0247**
		(0.0287)	(0.0228)	(0.0204)	(0.0227)	(0.0208)	(0.0280)	(0.0107)
	Q2	0.0301	0.0078	0.0168	0.0295	−0.0034	0.0335	0.0162
		(0.0215)	(0.0191)	(0.0237)	(0.0198)	(0.0168)	(0.0277)	(0.0106)
	Q3	−0.0102	0.0241	−0.0284*	−0.0480*	0.0133	−0.0235	−0.0098
		(0.0179)	(0.0152)	(0.0153)	(0.0250)	(0.0203)	(0.0269)	(0.0073)
	Q4	−0.0049	0.0116	−0.0095	−0.0236	−0.0419	0.0370	−0.0137
		(0.0161)	(0.0191)	(0.0188)	(0.0182)	(0.0305)	(0.0359)	(0.0112)
	Q5	−0.0131	0.0349*	−0.0090	−0.0538***	−0.0656**	0.0525	−0.0213**
		(0.0266)	(0.0186)	(0.0204)	(0.0200)	(0.0291)	(0.0438)	(0.0108)
	Q1–Q5	0.0505	−0.0240	0.0296	0.0796**	0.0942***		0.0460***
		(0.0312)	(0.0301)	(0.0267)	(0.0324)	(0.0361)		(0.0152)

Table 5: Further Double-Sorts

This table reports equally weighted (Panel A) and value-weighted (Panel B) Fama & French (2015) five-factor alphas for double-sorted portfolios. At the end of each month, we independently sort the stocks into five times five portfolios according to the characteristic denoted in the first column and their $LR_{VAR(1)}$. This results in a total of 25 portfolios. The portfolios reported are the respective averages of the $LR_{VAR(1)}$ quintiles across the quintiles sorted on the control variable. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1)}$, while controlling for the variable denoted in the first column. We hold the portfolios for one month. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Beta	0.0118	−0.0015	−0.0048	−0.0161	−0.0311**	0.0429***
	(0.0108)	(0.0088)	(0.0097)	(0.0130)	(0.0128)	(0.0140)
Book-to-market	0.0053	−0.0008	−0.0082	−0.0215*	−0.0340***	0.0393***
	(0.0094)	(0.0090)	(0.0102)	(0.0128)	(0.0128)	(0.0144)
Momentum	0.0125	0.0012	−0.0075	−0.0177	−0.0333***	0.0458***
	(0.0092)	(0.0094)	(0.0095)	(0.0121)	(0.0112)	(0.0118)
Short-term reversal	0.0099	0.0003	−0.0076	−0.0201	−0.0271**	0.0370***
	(0.0098)	(0.0088)	(0.0096)	(0.0124)	(0.0119)	(0.0130)
MAX	0.0094	−0.0010	−0.0076	−0.0195	−0.0313***	0.0407***
	(0.0098)	(0.0085)	(0.0091)	(0.0122)	(0.0118)	(0.0126)
Coskewness	0.0116	−0.0013	−0.0076	−0.0208*	−0.0294**	0.0410***
	(0.0103)	(0.0083)	(0.0096)	(0.0125)	(0.0121)	(0.0135)
DBeta	0.0117	−0.0008	−0.0072	−0.0177	−0.0307**	0.0424***
	(0.0107)	(0.0089)	(0.0092)	(0.0124)	(0.0119)	(0.0133)
Panel B: Value-Weighted:						
Beta	0.0197*	0.0094	−0.0161*	−0.0154	−0.0228**	0.0425***
	(0.0119)	(0.0143)	(0.0093)	(0.0115)	(0.0113)	(0.0147)
Book-to-market	0.0175*	0.0095	−0.0134	−0.0124	−0.0117	0.0293**
	(0.0102)	(0.0113)	(0.0083)	(0.0095)	(0.0111)	(0.0148)
Momentum	0.0219**	0.0075	−0.0077	−0.0133	−0.0181**	0.0400***
	(0.0100)	(0.0117)	(0.0078)	(0.0109)	(0.0091)	(0.0129)
Short-term reversal	0.0233**	0.0127	−0.0127*	−0.0109	−0.0106	0.0339**
	(0.0112)	(0.0121)	(0.0075)	(0.0095)	(0.0095)	(0.0137)
MAX	0.0272**	0.0136	−0.0011	−0.0002	−0.0052	0.0324**
	(0.0113)	(0.0127)	(0.0095)	(0.0131)	(0.0112)	(0.0132)
Coskewness	0.0234**	0.0109	−0.0061	−0.0045	−0.0033	0.0267*
	(0.0106)	(0.0110)	(0.0072)	(0.0096)	(0.0101)	(0.0136)
DBeta	0.0238**	0.0098	−0.0140*	−0.0112	−0.0158*	0.0396***
	(0.0110)	(0.0123)	(0.0074)	(0.0099)	(0.0091)	(0.0138)

Table 6: Fama–MacBeth Regressions

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions. Each month, we regress the excess stock returns over the next month on a constant, $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(1)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Constant	0.0795*	0.0746*	0.0764*	0.0707	0.0707	0.0747	0.0695	0.0724	0.0707	0.2782	0.2358	−0.4346
	(0.044)	(0.043)	(0.043)	(0.056)	(0.056)	(0.056)	(0.056)	(0.060)	(0.056)	(0.376)	(0.421)	(0.471)
$LR_{VAR(1)}$	−0.0133**	−0.0125**	−0.0115**	−0.0115**	−0.0125***	−0.0122***	−0.0119***	−0.0123***	−0.0116***	−0.0111***	−0.0146***	−0.0125***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Beta		−0.0124	−0.0157	−0.0191	−0.0308	−0.0304	−0.0247	−0.0219	−0.0316	−0.0158	−0.0294	−0.0003
		(0.029)	(0.029)	(0.029)	(0.027)	(0.026)	(0.024)	(0.021)	(0.027)	(0.027)	(0.027)	(0.029)
Size			−0.0012	−0.0018	−0.0028	−0.0029	−0.0037	−0.0040	−0.0026	−0.0027	−0.0022	−0.0041
			(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Book-to-market			0.0646	0.0073	−0.0299	−0.0357	−0.0237	−0.0444	−0.0183	0.0333	0.0262	0.0422
			(0.123)	(0.175)	(0.164)	(0.171)	(0.163)	(0.162)	(0.152)	(0.112)	(0.113)	(0.107)
BAS				−0.0174	−0.0170	−0.0064	−0.0125	0.0023	−0.0212	0.8526	0.1668	−7.0721
				(0.055)	(0.045)	(0.045)	(0.033)	(0.039)	(0.044)	(4.029)	(4.737)	(5.635)
Momentum					0.0253	0.0244	0.0286	0.0325*	0.0261	0.0268	0.0251	0.0310*
					(0.018)	(0.018)	(0.018)	(0.019)	(0.017)	(0.018)	(0.018)	(0.018)
Short-term reversal					−0.0245	−0.0254	−0.0295*	−0.0267*	−0.0255	−0.0257	−0.0263	−0.0295*
					(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Leverage						0.0034						0.0023
						(0.014)						(0.012)
IVol							−0.0101					−0.0034
							(0.023)					(0.018)
MAX								−0.0149				−0.0013
								(0.033)				(0.026)
Coskewness									0.0013			−0.0134
									(0.011)			(0.014)
Cokurtosis									−0.0085			0.0071
									(0.011)			(0.013)
DBeta										−0.0150		−0.0307
										(0.017)		(0.022)
Vol-of-vol											−0.0110**	−0.0072*
											(0.004)	(0.004)
Adj. R^2	0.0037	0.0523	0.0551	0.0569	0.0773	0.0812	0.0830	0.0850	0.0858	0.0811	0.0774	0.0997
t-statistic	[−2.244]	[−2.499]	[−2.297]	[−2.181]	[−2.815]	[−2.901]	[−2.861]	[−2.831]	[−2.671]	[−2.693]	[−3.276]	[−3.234]

Table 7: Fama–MacBeth Regressions with Option-Implied Control Variables

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions using further option-implied control variables. Each month, we regress the excess stock returns over the next month on a constant, $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. IV_{end}, IS_{end}, IK_{end} present the implied volatility, skewness, and kurtosis at the end of the previous month, respectively. IV_{mean}, IS_{mean}, IK_{mean} present the average implied volatility, skewness, and kurtosis of the previous month, respectively. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(1)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	0.0648	0.0674	0.0652	0.0648	0.0660	0.0685	0.0657	0.0634
	(0.057)	(0.056)	(0.056)	(0.057)	(0.056)	(0.055)	(0.056)	(0.057)
$LR_{VAR(1)}$	−0.0120***	−0.0081*	−0.0118**	−0.0076*	−0.0118***	−0.0099**	−0.0118***	−0.0090**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Beta	−0.0162	−0.0366	−0.0268	−0.0179	−0.0181	−0.0351	−0.0291	−0.0192
	(0.019)	(0.027)	(0.026)	(0.019)	(0.020)	(0.026)	(0.026)	(0.019)
Size	−0.0043	−0.0007	−0.0034	−0.0027	−0.0043	−0.0015	−0.0031	−0.0033
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Book-to-market	−0.0178	−0.0196	−0.0151	−0.0136	−0.0282	−0.0364	−0.0179	−0.0269
	(0.163)	(0.171)	(0.167)	(0.173)	(0.160)	(0.168)	(0.164)	(0.165)
BAS	−0.0077	−0.0418	−0.0280	−0.0166	−0.0064	−0.0333	−0.0226	−0.0099
	(0.033)	(0.045)	(0.048)	(0.033)	(0.030)	(0.042)	(0.046)	(0.030)
Momentum	0.0299	0.0255	0.0259	0.0300*	0.0297	0.0260	0.0257	0.0301*
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Short-term reversal	−0.0286*	−0.0205	−0.0248	−0.0265*	−0.0281*	−0.0240	−0.0248	−0.0273*
	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
IV_{end}	−0.0283			−0.0318				
	(0.023)			(0.024)				
IS_{end}		0.0310***		0.0288***				
		(0.005)		(0.004)				
IK_{end}			0.0084	−0.0011				
			(0.009)	(0.009)				
IV_{mean}					−0.0264			−0.0324
					(0.023)			(0.023)
IS_{mean}						0.0180**		0.0193***
						(0.008)		(0.006)
IK_{mean}							−0.0126	−0.0171
							(0.018)	(0.022)
Adj. R^2	0.0892	0.0785	0.0789	0.0903	0.0890	0.0786	0.0790	0.0903
t-statistic	[−2.763]	[−1.704]	[−2.596]	[−1.699]	[−2.778]	[−2.064]	[−2.627]	[−2.036]

Table 8: Summary Statistics and Correlations – Moment Persistence

This table presents summary statistics for (Panel A) and correlations among (Panel B) the LR^*_{Vol}, LR^*_{Skew}, and LR^*_{Kurt} measures. Mean is the time-series average of the cross-sectional average. Std., Skewness, and Kurtosis present the average cross-sectional standard deviation, skewness, and kurtosis, respectively. Min and Max report the time-series average of the minimum and maximum observation in the cross-section. 5%, 25%, Median, 75% and 95% indicate the averages of the corresponding cross-sectional quantiles, respectively. $LR^*_{VAR(1)}$, LR^*_{Vol}, LR^*_{Skew}, and LR^*_{Kurt} denote the raw (non-standardized) $LR_{VAR(1)}$, LR_{Vol}, LR_{Skew}, and LR_{Kurt} measures, respectively. Panel B presents the average cross-sectional correlations of the respective variables. The sample period is January 1996 until December 2016.

Panel A: Summary Statistics:

	Mean	Std.	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
$LR^*_{VAR(1)}$	978	352	0.00	2.46	3.13	389	740	984	1,209	1,561	2,200
LR^*_{Vol}	607	241	0.02	2.42	−2.05	191	437	623	787	973	1,253
LR^*_{Skew}	193	149	0.54	2.89	−2.37	25.5	86.7	155	259	495	944
LR^*_{Kurt}	195	149	0.56	2.98	−2.39	19.9	83.9	161	271	489	908

Panel B: Correlations:

	$LR_{VAR(1)}$	LR_{Vol}	LR_{Skew}	LR_{Kurt}
$LR_{VAR(1)}$	*	0.86	0.66	0.67
LR_{Vol}		*	0.36	0.46
LR_{Skew}			*	0.68
LR_{Kurt}				*

Table 9: Sorted Portfolios – Moment Persistence

At the end of each month, we sort the stocks into five portfolios according to their LR_{Vol}, LR_{Skew}, and LR_{Kurt}. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest sorting characteristic and simultaneously selling the stocks in the quintile with the highest sorting characteristic. Panels A–D present the results for equally weighted portfolio sorts while in Panels E–F we weigh the stocks in each portfolio according to their market value. We hold the portfolios for one month. The row labeled FF5 alpha refers to the alphas the Fama & French (2015) five-factor model. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: LR_{Vol} – Equally Weighted:						
Average Return	0.0851**	0.0903**	0.0806*	0.0755	0.0665	0.0186
	(0.0431)	(0.0428)	(0.0442)	(0.0468)	(0.0477)	(0.0156)
FF5 alpha	0.0028	−0.0012	−0.0103	−0.0171	−0.0233*	0.0261*
	(0.0095)	(0.0084)	(0.0117)	(0.0117)	(0.0132)	(0.0145)
Panel B: LR_{Skew} – Equally Weighted:						
Average Return	0.0999**	0.1010**	0.0759*	0.0704	0.0509	0.0490**
	(0.0432)	(0.0420)	(0.0425)	(0.0443)	(0.0537)	(0.0226)
FF5 alpha	0.0012	0.0068	−0.0166	−0.0201**	−0.0203	0.0215
	(0.0095)	(0.0106)	(0.0105)	(0.0101)	(0.0127)	(0.0141)
Panel C: LR_{Kurt} – Equally Weighted:						
Average Return	0.0970**	0.0978**	0.0862**	0.0725*	0.0446	0.0524***
	(0.0459)	(0.0440)	(0.0431)	(0.0432)	(0.0497)	(0.0186)
FF5 alpha	0.0036	0.0005	−0.0111	−0.0166	−0.0255**	0.0290*
	(0.0113)	(0.0115)	(0.0116)	(0.0112)	(0.0124)	(0.0174)
Panel D: LR_{Vol} – Value-Weighted:						
Average Return	0.0848**	0.0756*	0.0557	0.0624	0.0710	0.0138
	(0.0372)	(0.0386)	(0.0397)	(0.0396)	(0.0434)	(0.0171)
FF5 alpha	0.0091	0.0070	−0.0135	−0.0051	−0.0030	0.0121
	(0.0107)	(0.0124)	(0.0098)	(0.0065)	(0.0137)	(0.0189)
Panel E: LR_{Skew} – Value-Weighted:						
Average Return	0.0799**	0.0838**	0.0617*	0.0556	0.0548	0.0251
	(0.0392)	(0.0368)	(0.0366)	(0.0405)	(0.0467)	(0.0220)
FF5 alpha	0.0021	0.0074	−0.0174*	−0.0161*	−0.0037	0.0057
	(0.0127)	(0.0100)	(0.0089)	(0.0094)	(0.0113)	(0.0198)
Panel F: LR_{Kurt} – Value-Weighted:						
Average Return	0.0830*	0.0864**	0.0676*	0.0610	0.0441	0.0389**
	(0.0448)	(0.0393)	(0.0370)	(0.0389)	(0.0417)	(0.0184)
FF5 alpha	0.0040	0.0102	−0.0089	−0.0078	−0.0159*	0.0198
	(0.0176)	(0.0129)	(0.0112)	(0.0109)	(0.0086)	(0.0226)

Asset Prices and "the Devil(s) You Know"

Online Appendix

JEL classification: G12, G11, G10

Keywords: Persistence, stock return distribution, option-implied central moments, asset pricing

A1 Sample Summary Statistics

Table A1: Sample Summary Statistics

This table presents summary statistics for our main sample. At the end of December in each year (indicated in the first column), we provide the number of stocks for which we have data on $LR_{VAR(1)}$ after applying all filters (# Stocks). In addition, we present the share of the total market capitalization of the stocks in our sample relative to the whole universe of all NYSE, AMEX, and NASDAQ stocks available on CRSP (excluding closed-end funds and REITs) (Share MC). Finally, we provide the average market capitalization (in billions of USD) for the stocks included in our sample (Avg. MC_{sample}) as well as the total CRSP sample (Avg. MC_{tot}). The row denoted 'Avg.' displays the time-series averages of the respective statistics over our sample period.

Date	# Stocks	Share MC	Avg. MC_{sample}	Avg. MC_{tot}
12.1996	1,329	0.80	5.12	0.99
12.1997	1,618	0.84	5.84	1.28
12.1998	1,655	0.87	7.34	1.67
12.1999	1,797	0.84	8.71	2.28
12.2000	1,496	0.86	9.66	2.14
12.2001	1,468	0.85	8.40	2.09
12.2002	1,319	0.84	7.06	1.77
12.2003	1,590	0.84	7.82	2.49
12.2004	1,665	0.84	8.34	2.82
12.2005	1,790	0.84	8.40	3.01
12.2006	1,927	0.85	8.81	3.41
12.2007	1,966	0.86	9.16	3.60
12.2008	1,473	0.83	6.89	2.25
12.2009	1,826	0.88	7.47	3.06
12.2010	1,974	0.89	8.18	3.61
12.2011	1,893	0.90	8.31	3.53
12.2012	2,019	0.91	9.05	4.02
12.2013	2,348	0.91	10.1	5.12
12.2014	2,355	0.91	11.0	5.40
12.2015	2,282	0.91	10.8	5.10
12.2016	2,379	0.92	11.1	5.62
Avg.	1,807	0.87	8.43	3.08

A2 Full Double Sorts – Equally Weighted

Table A2: Double-Sorted Portfolios – Equally Weighted

This table reports equally weighted Fama & French (2015) five-factor alphas for double-sorted portfolios. At the end of each month, we independently sort the stocks into five times five portfolios according to the characteristic denoted in the panel headings and their $LR_{VAR(1)}$. This results in a total of 25 portfolios. The row (column) labeled Q1–Q5 refers to the hedge portfolios for $LR_{VAR(1)}$ (the control variable). The column Avg. presents the average of the $LR_{VAR(1)}$ quintiles across the five quintiles of the control variable. We hold the portfolios for one month. We perform double sorts on size (Panel A), BAS (Panel B), iVol (Panel C), and Vol-of-Vol (Panel D). Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Size:

		Size						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0103	−0.0049	0.0236*	0.0184	0.0251	−0.0148	0.0145
		(0.0169)	(0.0133)	(0.0141)	(0.0143)	(0.0201)	(0.0252)	(0.0107)
	Q2	0.0094	−0.0205*	−0.0103	0.0046	0.0148	−0.0053	−0.0004
		(0.0146)	(0.0122)	(0.0130)	(0.0136)	(0.0132)	(0.0189)	(0.0088)
	Q3	−0.0240	−0.0162	−0.0132	0.0139	−0.0020	−0.0220	−0.0083
		(0.0180)	(0.0151)	(0.0147)	(0.0157)	(0.0097)	(0.0190)	(0.0097)
	Q4	−0.0550**	−0.0183	−0.0492***	−0.0004	−0.0045	−0.0505*	−0.0255*
		(0.0267)	(0.0200)	(0.0187)	(0.0154)	(0.0117)	(0.0291)	(0.0134)
	Q5	−0.0862***	−0.0707***	−0.0376*	−0.0082	−0.0115	−0.0748**	−0.0428***
		(0.0259)	(0.0226)	(0.0225)	(0.0186)	(0.0135)	(0.0309)	(0.0142)
	Q1–Q5	0.0965***	0.0658**	0.0612**	0.0266	0.0366*		0.0573***
		(0.0315)	(0.0266)	(0.0236)	(0.0198)	(0.0199)		(0.0161)

Panel B: Bid-Ask Spread:

		BAS						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0612***	0.0336	0.0078	−0.0101	−0.0138	0.0750***	0.0157
		(0.0227)	(0.0208)	(0.0143)	(0.0140)	(0.0178)	(0.0283)	(0.0111)
	Q2	0.0441**	0.0227	−0.0000	−0.0307**	−0.0249	0.0690**	0.0022
		(0.0205)	(0.0140)	(0.0154)	(0.0139)	(0.0207)	(0.0341)	(0.0088)
	Q3	0.0516**	0.0035	−0.0057	−0.0520***	−0.0304	0.0820***	−0.0066
		(0.0199)	(0.0180)	(0.0162)	(0.0165)	(0.0198)	(0.0282)	(0.0098)
	Q4	0.0270	−0.0103	−0.0148	−0.0361*	−0.0584**	0.0854***	−0.0185
		(0.0182)	(0.0214)	(0.0224)	(0.0212)	(0.0226)	(0.0279)	(0.0141)
	Q5	0.0264	−0.0090	−0.0256	−0.0770***	−0.1090***	0.1355***	−0.0388***
		(0.0174)	(0.0171)	(0.0259)	(0.0242)	(0.0264)	(0.0347)	(0.0143)
	Q1–Q5	0.0348*	0.0426	0.0334	0.0669***	0.0952***		0.0546***
		(0.0186)	(0.0303)	(0.0257)	(0.0250)	(0.0276)		(0.0176)

Table A2: Double-Sorted Portfolios – Equally Weighted (continued)

Panel C: Idiosyncratic Volatility:

		iVol						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0118	−0.0115	0.0173	0.0091	0.0170	−0.0051	0.0087
		(0.0123)	(0.0146)	(0.0143)	(0.0147)	(0.0221)	(0.0252)	(0.0101)
	Q2	0.0003	0.0128	0.0055	−0.0026	−0.0253	0.0256	−0.0019
		(0.0116)	(0.0129)	(0.0130)	(0.0142)	(0.0175)	(0.0198)	(0.0089)
	Q3	−0.0071	−0.0002	−0.0149	−0.0020	−0.0114	0.0044	−0.0071
		(0.0127)	(0.0129)	(0.0161)	(0.0135)	(0.0208)	(0.0266)	(0.0095)
	Q4	0.0148	−0.0225	−0.0175	−0.0147	−0.0584***	0.0732***	−0.0196
		(0.0120)	(0.0138)	(0.0176)	(0.0194)	(0.0216)	(0.0202)	(0.0122)
	Q5	−0.0033	−0.0135	−0.0296*	−0.0334*	−0.0609**	0.0576**	−0.0282**
		(0.0127)	(0.0121)	(0.0174)	(0.0191)	(0.0254)	(0.0275)	(0.0116)
	Q1–Q5	0.0152	0.0020	0.0469**	0.0426**	0.0779***		0.0369***
		(0.0153)	(0.0143)	(0.0195)	(0.0215)	(0.0291)		(0.0129)

Panel D: Vol-of-Vol:

		Vol-of-vol						
		Q1	Q2	Q3	Q4	Q5	Q1–Q5	Avg.
$LR_{VAR(1)}$	Q1	0.0079	0.0143	0.0079	0.0196	0.0124	−0.0045	0.0124
		(0.0213)	(0.0128)	(0.0123)	(0.0126)	(0.0164)	(0.0170)	(0.0096)
	Q2	0.0016	0.0163	0.0013	−0.0034	0.0054	−0.0038	0.0042
		(0.0151)	(0.0143)	(0.0134)	(0.0137)	(0.0119)	(0.0143)	(0.0092)
	Q3	−0.0124	−0.0002	−0.0058	−0.0412***	0.0114	−0.0238	−0.0097
		(0.0167)	(0.0134)	(0.0135)	(0.0149)	(0.0155)	(0.0202)	(0.0099)
	Q4	0.0176	−0.0086	−0.0219	−0.0378**	−0.0885***	0.1061***	−0.0278**
		(0.0151)	(0.0149)	(0.0166)	(0.0150)	(0.0253)	(0.0229)	(0.0135)
	Q5	−0.0158	−0.0132	−0.0235	−0.0593***	−0.0782***	0.0624**	−0.0380***
		(0.0160)	(0.0128)	(0.0184)	(0.0200)	(0.0255)	(0.0279)	(0.0132)
	Q1–Q5	0.0237	0.0275	0.0315	0.0788***	0.0906***		0.0504***
		(0.0251)	(0.0180)	(0.0236)	(0.0210)	(0.0277)		(0.0147)

A3 Rebalancing Only in January

Table A3: Portfolio Sorts – Rebalancing Only in January

At the end of every January, we sort the stocks into five portfolios according to their $LR_{VAR(1)}$. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1)}$. Panel A presents the results for equally weighted portfolio sorts while in Panel B we weigh the stocks in each portfolio according to their market value. We hold the portfolios for twelve months, but base the inference on one-month returns. The row labeled Average Return return denotes the average portfolio excess return. CAPM alpha, FF3 alpha, four-factor alpha, five-factor alpha, and FF5 alpha refer to the alphas of the CAPM, the Fama & French (1993) three-factor the Carhart (1997) four-factor model, the five-factor model (including Pástor & Stambaugh, 2003 liquidity), and the Fama & French (2015) five-factor model, respectively. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Average Return	0.0938**	0.0925**	0.0850*	0.0766*	0.0619	0.0319*
	(0.0409)	(0.0416)	(0.0438)	(0.0454)	(0.0486)	(0.0166)
CAPM alpha	0.0233	0.0196	0.0099	−0.0008	−0.0212	0.0445***
	(0.0173)	(0.0175)	(0.0188)	(0.0176)	(0.0160)	(0.0139)
FF3 alpha	0.0108	0.0090	−0.0005	−0.0112	−0.0289**	0.0397***
	(0.0100)	(0.0118)	(0.0149)	(0.0140)	(0.0142)	(0.0123)
four-factor alpha	0.0156	0.0172	0.0126	0.0043	−0.0075	0.0231**
	(0.0115)	(0.0116)	(0.0137)	(0.0117)	(0.0109)	(0.0103)
five-factor alpha	0.0115	0.0103	0.0055	−0.0025	−0.0119	0.0234**
	(0.0112)	(0.0111)	(0.0132)	(0.0111)	(0.0104)	(0.0103)
FF5 alpha	0.0077	0.0064	−0.0075	−0.0090	−0.0200	0.0277**
	(0.0103)	(0.0110)	(0.0135)	(0.0140)	(0.0157)	(0.0134)
Panel B: Value-Weighted:						
Average Return	0.0925**	0.0734*	0.0623*	0.0699*	0.0486	0.0439***
	(0.0385)	(0.0397)	(0.0375)	(0.0389)	(0.0424)	(0.0165)
CAPM alpha	0.0296**	0.0057	−0.0015	0.0058	−0.0186*	0.0482***
	(0.0126)	(0.0107)	(0.0087)	(0.0093)	(0.0096)	(0.0166)
FF3 alpha	0.0219**	0.0097	−0.0023	0.0049	−0.0149*	0.0368***
	(0.0105)	(0.0110)	(0.0085)	(0.0088)	(0.0084)	(0.0127)
four-factor alpha	0.0175	0.0102	−0.0006	0.0059	−0.0153*	0.0328**
	(0.0111)	(0.0127)	(0.0090)	(0.0090)	(0.0089)	(0.0138)
five-factor alpha	0.0123	0.0015	−0.0034	0.0022	−0.0165*	0.0288**
	(0.0109)	(0.0109)	(0.0088)	(0.0087)	(0.0092)	(0.0137)
FF5 alpha	0.0138	0.0106	−0.0107	0.0022	−0.0156*	0.0295**
	(0.0131)	(0.0125)	(0.0080)	(0.0101)	(0.0092)	(0.0141)

A4 Further Control Variables

Table A4: Double-Sorted Portfolios Returns – Further Control Variables

This table reports equally weighted Fama & French (2015) five-factor alphas for double-sorted portfolios using further control variables. At the end of each month, we independently sort the stocks into five times five portfolios according to the characteristic denoted in the first column and their $LR_{VAR(1)}$. This results in a total of 25 portfolios. The portfolios reported are the respective averages of the $LR_{VAR(1)}$ quintiles across the quintiles sorted on the control variable. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1)}$, while controlling for the variable denoted in the first column. We hold the portfolios for one month. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Age	0.0103	0.0004	−0.0066	−0.0191	−0.0326***	0.0429***
	(0.0096)	(0.0094)	(0.0100)	(0.0125)	(0.0125)	(0.0141)
BNS	0.0107	−0.0012	−0.0077	−0.0211	−0.0292**	0.0399***
	(0.0102)	(0.0084)	(0.0097)	(0.0129)	(0.0123)	(0.0138)
Dispersion	0.0074	0.0000	−0.0074	−0.0205	−0.0254**	0.0328**
	(0.0097)	(0.0095)	(0.0096)	(0.0127)	(0.0116)	(0.0130)
EIS	0.0103	0.0009	−0.0075	−0.0204	−0.0252**	0.0355***
	(0.0100)	(0.0087)	(0.0096)	(0.0124)	(0.0116)	(0.0125)
VRP	0.0082	0.0023	−0.0112	−0.0179	−0.0324***	0.0406***
	(0.0101)	(0.0090)	(0.0094)	(0.0127)	(0.0124)	(0.0143)

Table A5: Fama–MacBeth Regressions – Further Control Variables

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions using further control variables. Each month, we regress the excess stock returns over the next month on a constant, $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled *t*-statistic presents the *t*-statistic for the premium on $LR_{VAR(1)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Constant	0.0723	0.0684	0.0723	0.0701	0.0649	0.0714
	(0.055)	(0.056)	(0.061)	(0.055)	(0.057)	(0.060)
$LR_{VAR(1)}$	−0.0125***	−0.0125***	−0.0123***	−0.0127***	−0.0129***	−0.0125**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Beta	−0.0303	−0.0319	−0.0311	−0.0316	−0.0290	−0.0308
	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)	(0.025)
Size	−0.0032	−0.0017	−0.0027	−0.0024	−0.0030	−0.0021
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Book-to-market	−0.0287	−0.0160	−0.0398	−0.0364	−0.0233	−0.0319
	(0.166)	(0.161)	(0.176)	(0.163)	(0.165)	(0.175)
BAS	−0.0106	−0.0190	−0.0118	−0.0236	−0.0314	−0.0119
	(0.041)	(0.045)	(0.063)	(0.040)	(0.046)	(0.057)
Momentum	0.0258	0.0260	0.0295	0.0286	0.0279	0.0367*
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Short-term reversal	−0.0253	−0.0242	−0.0254*	−0.0280*	−0.0255	−0.0310**
	(0.016)	(0.016)	(0.015)	(0.015)	(0.017)	(0.015)
Age	0.0028					0.0036
	(0.004)					(0.004)
BNS		−0.1005***				−0.1122***
		(0.025)				(0.025)
Dispersion			−0.0009			0.0015
			(0.008)			(0.008)
EIS				0.0127		0.0143
				(0.012)		(0.012)
VRP					−0.0164	−0.0151
					(0.013)	(0.012)
Adj. R^2	0.0797	0.0919	0.0794	0.0818	0.0795	0.1041
t-statistic	[−2.787]	[−2.780]	[−2.656]	[−2.912]	[−2.801]	[−2.598]

A5 Implied vs. Realized Moments

Table A6: Predicting Realized Moments with Realized and Implied Moments

This table presents results for predictability regressions of realized volatility, skewness, and kurtosis. For each stock, we regress the realized monthly moment calculated from daily returns on lagged realized moments or lagged implied moments obtained from options data. We report the adj. R^2 for the regressions with the implied predictors (I.P.) or realized predictors (R.P.) in the first and second column, respectively. The last column reports the t-statistic for the difference between the adj. R^2 using implied predictors and the adj. R^2 using realized predictors.

	adj. R^2 I.P.	adj. R^2 R.P.	t-stat (difference of adj. R^2)
Volatility	0.1877	0.1667	7.6458
Skewness	0.0014	−0.0023	2.5468
Kurtosis	0.0014	−0.0046	3.8313

A6 Alternative Holding Period

Table A7: Portfolio Sorts – Three-Month Holding Period

At the end of each month, we sort the stocks into five portfolios according to their $LR_{VAR(1)}$. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1)}$. Panel A presents the results for equally weighted portfolio sorts while in Panel B we weigh the stocks in each portfolio according to their market value. We hold the portfolios for three months. The row labeled Average Return return denotes the average portfolio excess return. CAPM alpha, FF3 alpha, four-factor alpha, five-factor alpha, and FF5 alpha refer to the alphas of the CAPM, the Fama & French (1993) three-factor the Carhart (1997) four-factor model, the five-factor model (including Pástor & Stambaugh, 2003 liquidity), and the Fama & French (2015) five-factor model, respectively. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Average Return	0.0943**	0.0880**	0.0807**	0.0731*	0.0594	0.0349**
	(0.0380)	(0.0386)	(0.0397)	(0.0418)	(0.0461)	(0.0164)
CAPM alpha	0.0238	0.0158	0.0061	−0.0047	−0.0249*	0.0488***
	(0.0158)	(0.0153)	(0.0140)	(0.0149)	(0.0133)	(0.0136)
FF3 alpha	0.0123	0.0049	−0.0035	−0.0142	−0.0309***	0.0432***
	(0.0080)	(0.0083)	(0.0091)	(0.0116)	(0.0116)	(0.0119)
four-factor alpha	0.0108	0.0099	0.0037	−0.0020	−0.0189*	0.0298**
	(0.0090)	(0.0084)	(0.0088)	(0.0101)	(0.0105)	(0.0121)
five-factor alpha	0.0078	0.0045	0.0004	−0.0063	−0.0216**	0.0294**
	(0.0091)	(0.0081)	(0.0089)	(0.0099)	(0.0101)	(0.0120)
FF5 alpha	0.0053	−0.0012	−0.0092	−0.0195*	−0.0258**	0.0310**
	(0.0089)	(0.0084)	(0.0087)	(0.0105)	(0.0124)	(0.0139)
Panel B: Value-Weighted:						
Average Return	0.0970***	0.0835**	0.0590*	0.0637*	0.0604	0.0366**
	(0.0323)	(0.0335)	(0.0339)	(0.0370)	(0.0414)	(0.0183)
CAPM alpha	0.0359***	0.0206*	−0.0035	−0.0027	−0.0122	0.0481***
	(0.0111)	(0.0105)	(0.0068)	(0.0087)	(0.0104)	(0.0163)
FF3 alpha	0.0298***	0.0186*	−0.0052	−0.0045	−0.0074	0.0372***
	(0.0091)	(0.0101)	(0.0055)	(0.0080)	(0.0095)	(0.0123)
four-factor alpha	0.0256***	0.0194*	−0.0052	−0.0029	−0.0099	0.0356***
	(0.0094)	(0.0099)	(0.0060)	(0.0084)	(0.0095)	(0.0132)
five-factor alpha	0.0213**	0.0121	−0.0072	−0.0049	−0.0128	0.0341**
	(0.0091)	(0.0090)	(0.0060)	(0.0087)	(0.0097)	(0.0133)
FF5 alpha	0.0178	0.0124	−0.0125*	−0.0059	−0.0052	0.0231*
	(0.0115)	(0.0121)	(0.0064)	(0.0094)	(0.0099)	(0.0137)

Table A8: Fama–MacBeth Regressions – Three-Month Holding Period

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions. Each month, we regress the excess stock returns over the next three months on a constant, $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(1)}$.

Factor	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Constant	0.0784*	0.0803**	0.0812**	0.0722	0.0727	0.0766	0.0720	0.0759	0.0727	0.6106*	0.6728*	0.1650
	(0.041)	(0.039)	(0.039)	(0.049)	(0.050)	(0.050)	(0.051)	(0.054)	(0.051)	(0.345)	(0.395)	(0.258)
$LR_{VAR(1)}$	−0.0104*	−0.0102**	−0.0094**	−0.0095**	−0.0099**	−0.0097***	−0.0095**	−0.0098**	−0.0095**	−0.0088**	−0.0110***	−0.0095***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Beta		−0.0051	−0.0072	−0.0106	−0.0209	−0.0204	−0.0144	−0.0121	−0.0217	−0.0037	−0.0192	0.0118
		(0.026)	(0.026)	(0.026)	(0.023)	(0.023)	(0.021)	(0.018)	(0.023)	(0.023)	(0.024)	(0.026)
Size			−0.0019	−0.0025	−0.0029	−0.0031	−0.0040	−0.0042	−0.0030	−0.0030	−0.0024	−0.0045*
			(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Book-to-market			−0.0136	−0.0733	−0.1514	−0.1487	−0.1419	−0.1581	−0.1546	−0.0616	−0.0602	−0.0436
			(0.105)	(0.140)	(0.149)	(0.154)	(0.154)	(0.154)	(0.143)	(0.094)	(0.096)	(0.094)
BAS				−0.0211	−0.0191	−0.0098	−0.0117	0.0036	−0.0202	5.9942	6.8762	0.9098
				(0.039)	(0.034)	(0.035)	(0.026)	(0.029)	(0.034)	(3.819)	(4.370)	(2.722)
Momentum					0.0242	0.0235	0.0260*	0.0314**	0.0245*	0.0255*	0.0248*	0.0288*
					(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Short-term reversal					−0.0031	−0.0043	−0.0022	−0.0019	−0.0022	−0.0026	−0.0039	−0.0021
					(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Leverage						0.0042						0.0043
						(0.012)						(0.011)
IVol							−0.0149					−0.0087
							(0.019)					(0.013)
MAX								−0.0180				−0.0041
								(0.028)				(0.021)
Coskewness									0.0035			−0.0163
									(0.009)			(0.015)
Cokurtosis									−0.0060			0.0128
									(0.009)			(0.012)
DBeta										−0.0185		−0.0335
										(0.014)		(0.022)
Vol-of-vol											−0.0078***	−0.0050*
											(0.003)	(0.003)
Adj. R^2	0.0031	0.0515	0.0550	0.0573	0.0762	0.0804	0.0825	0.0844	0.0840	0.0792	0.0758	0.0991
t-statistic	[−1.895]	[−2.314]	[−2.099]	[−2.059]	[−2.581]	[−2.675]	[−2.595]	[−2.561]	[−2.526]	[−2.378]	[−2.781]	[−2.676]

Table A9: Fama–MacBeth Regressions II – Three-Month Holding Period

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions using further option-implied control variables. Each month, we regress the excess stock returns over the next three months on a constant, $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. IV_{end}, IS_{end}, IK_{end} present the implied volatility, skewness, and kurtosis at the end of the previous month, respectively. IV_{mean}, IS_{mean}, IK_{mean} present the average implied volatility, skewness, and kurtosis of the previous month, respectively. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(1)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	0.0758	0.0711	0.0705	0.0757	0.0777	0.0721	0.0690	0.0732
	(0.048)	(0.047)	(0.047)	(0.048)	(0.048)	(0.047)	(0.047)	(0.048)
$LR_{VAR(1)}$	−0.0090**	−0.0071*	−0.0095**	−0.0063*	−0.0091***	−0.0078**	−0.0099***	−0.0072**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Beta	−0.0098	−0.0243	−0.0202	−0.0115	−0.0100	−0.0241	−0.0214	−0.0116
	(0.016)	(0.022)	(0.021)	(0.016)	(0.016)	(0.021)	(0.021)	(0.016)
Size	−0.0042*	−0.0018	−0.0031	−0.0030	−0.0042*	−0.0020	−0.0029	−0.0032
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Book-to-market	−0.1415	−0.1409	−0.1407	−0.1331	−0.1432	−0.1531	−0.1405	−0.1410
	(0.163)	(0.146)	(0.147)	(0.160)	(0.161)	(0.151)	(0.146)	(0.161)
BAS	0.0089	−0.0335	−0.0233	0.0050	0.0141	−0.0292	−0.0201	0.0110
	(0.026)	(0.030)	(0.031)	(0.026)	(0.025)	(0.029)	(0.031)	(0.025)
Momentum	0.0287**	0.0247*	0.0249*	0.0287**	0.0288**	0.0251*	0.0248*	0.0292**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Short-term reversal	−0.0036	−0.0006	−0.0027	−0.0019	−0.0040	−0.0026	−0.0031	−0.0029
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)
IV_{end}	−0.0236			−0.0295				
	(0.019)			(0.019)				
IS_{end}		0.0179***		0.0191***				
		(0.004)		(0.003)				
IK_{end}			0.0002	−0.0080				
			(0.006)	(0.005)				
IV_{mean}					−0.0239			−0.0322
					(0.019)			(0.019)
IS_{mean}						0.0151***		0.0143***
						(0.005)		(0.005)
IK_{mean}							−0.0210	−0.0315*
							(0.015)	(0.018)
Adj. R^2	0.0881	0.0774	0.0781	0.0891	0.0882	0.0774	0.0784	0.0895
t-statistic	[−2.542]	[−1.800]	[−2.588]	[−1.728]	[−2.638]	[−1.980]	[−2.710]	[−1.996]

A7 Alternative Option-Implied Horizons

Table A10: Summary Statistics – Alternative Option-Implied Horizons

This table presents summary statistics for (Panel A) and correlations among (Panel B) the $LR_{VAR(1)}$ measures for different option-implied horizons. Mean is the time-series average of the cross-sectional average. Std., Skewness, and Kurtosis present the average cross-sectional standard deviation, skewness, and kurtosis, respectively. Min and Max report the time-series average of the minimum and maximum observation in the cross-section. 5%, 25%, Median, 75% and 95% indicate the averages of the corresponding cross-sectional quantiles, respectively. $LR^{*}_{VAR(1)}$ denotes the raw (non-standardized) $LR_{VAR(1)}$ measure. Panel B presents the average cross-sectional correlations of the respective variables. The sample period is January 1996 until December 2016.

Panel A: Summary Statistics:

	Mean	Std.	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
$LR^{*}_{VAR(1)}$	978	352	0.00	2.46	3.13	389	740	984	1,209	1,561	2,200
$LR^{*}_{VAR(1),182-day}$	985	337	−0.04	2.46	3.66	404	761	999	1,211	1,522	2,142
$LR^{*}_{VAR(1),91-day}$	923	310	−0.05	2.46	3.88	387	720	936	1,130	1,419	1,957
$LR^{*}_{VAR(1),30-day}$	690	249	−0.03	2.47	3.24	259	519	707	861	1,081	1,523

Panel B: Correlations:

	$LR_{VAR(1)}$	$LR_{VAR(1),182-day}$	$LR_{VAR(1),91-day}$	$LR_{VAR(1),30-day}$
$LR_{VAR(1)}$	*	0.93	0.84	0.71
$LR_{VAR(1),182-day}$		*	0.91	0.75
$LR_{VAR(1),91-day}$			*	0.80
$LR_{VAR(1),30-day}$				*

Table A11: Portfolio Sorts – 30-Day Option-Implied Horizon

At the end of each month, we sort the stocks into five portfolios according to their $LR_{VAR(1),30-day}$ based on 30-day option-implied moments. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(1),30-day}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(1),30-day}$. Panel A presents the results for equally weighted portfolio sorts while in Panel B we weigh the stocks in each portfolio according to their market value. We hold the portfolios for one month. The row labeled Average Return return denotes the average portfolio excess return. CAPM alpha, FF3 alpha, four-factor alpha, five-factor alpha, and FF5 alpha refer to the alphas of the CAPM, the Fama & French (1993) three-factor the Carhart (1997) four-factor model, the five-factor model (including Pástor & Stambaugh, 2003 liquidity), and the Fama & French (2015) five-factor model, respectively. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Average Return	0.0877**	0.0783*	0.0856*	0.0792*	0.0583	0.0294**
	(0.0423)	(0.0459)	(0.0458)	(0.0456)	(0.0474)	(0.0134)
CAPM alpha	0.0155	−0.0001	0.0053	−0.0017	−0.0221	0.0376***
	(0.0146)	(0.0155)	(0.0169)	(0.0159)	(0.0175)	(0.0128)
FF3 alpha	0.0041	−0.0098	−0.0043	−0.0110	−0.0318**	0.0359***
	(0.0076)	(0.0095)	(0.0124)	(0.0114)	(0.0148)	(0.0121)
four-factor alpha	0.0044	−0.0078	0.0013	−0.0032	−0.0202	0.0246**
	(0.0087)	(0.0099)	(0.0118)	(0.0106)	(0.0131)	(0.0106)
five-factor alpha	0.0005	−0.0102	−0.0036	−0.0094	−0.0262**	0.0267**
	(0.0086)	(0.0098)	(0.0115)	(0.0100)	(0.0126)	(0.0106)
FF5 alpha	0.0044	−0.0111	−0.0050	−0.0168	−0.0335**	0.0379***
	(0.0082)	(0.0088)	(0.0109)	(0.0105)	(0.0146)	(0.0125)
Panel B: Value-Weighted:						
Average Return	0.0804**	0.0684*	0.0678*	0.0781**	0.0484	0.0320*
	(0.0370)	(0.0394)	(0.0399)	(0.0383)	(0.0434)	(0.0165)
CAPM alpha	0.0176	0.0024	−0.0000	0.0103	−0.0225**	0.0401**
	(0.0112)	(0.0096)	(0.0086)	(0.0088)	(0.0113)	(0.0155)
FF3 alpha	0.0110	0.0024	0.0018	0.0119	−0.0203*	0.0313**
	(0.0102)	(0.0096)	(0.0085)	(0.0087)	(0.0113)	(0.0146)
four-factor alpha	0.0119	0.0004	0.0006	0.0054	−0.0168	0.0287*
	(0.0118)	(0.0094)	(0.0085)	(0.0084)	(0.0113)	(0.0159)
five-factor alpha	0.0112	−0.0006	−0.0021	0.0022	−0.0198*	0.0309**
	(0.0118)	(0.0090)	(0.0090)	(0.0083)	(0.0111)	(0.0151)
FF5 alpha	0.0061	−0.0020	0.0022	0.0056	−0.0214*	0.0275*
	(0.0115)	(0.0098)	(0.0086)	(0.0098)	(0.0118)	(0.0160)

Table A12: Fama–MacBeth Regressions – Alternative Option-Implied Horizons

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions using $LR_{VAR(1)}$ derived from different option-implied horizons. Each month, we regress the excess stock returns over the next month on a constant, a $LR_{VAR(1)}$, as well as a series of control variables, all measured at the end of the current month. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(1)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	0.0777*	0.0792*	0.0794*	0.0795*	0.0793	0.0760	0.0740	0.0753
	(0.045)	(0.044)	(0.044)	(0.044)	(0.061)	(0.061)	(0.061)	(0.061)
$LR_{VAR(1),30-day}$	−0.0089*				−0.0083**			
	(0.005)				(0.004)			
$LR_{VAR(1),91-day}$		−0.0133***				−0.0109***		
		(0.005)				(0.004)		
$LR_{VAR(1),182-day}$			−0.0144***				−0.0121***	
			(0.005)				(0.004)	
$LR_{VAR(1)}$				−0.0133**				−0.0125***
				(0.006)				(0.004)
Beta					−0.0053	−0.0036	−0.0031	−0.0027
					(0.029)	(0.029)	(0.029)	(0.029)
Size					−0.0051*	−0.0048*	−0.0047*	−0.0041
					(0.003)	(0.003)	(0.003)	(0.003)
Book-to-market					−0.0125	−0.0042	−0.0089	−0.0209
					(0.155)	(0.151)	(0.156)	(0.158)
BAS					0.0087	−0.0017	−0.0053	0.0008
					(0.034)	(0.034)	(0.034)	(0.034)
Momentum					0.0316*	0.0318*	0.0319*	0.0323*
					(0.018)	(0.018)	(0.018)	(0.018)
Short-term reversal					−0.0287*	−0.0292*	−0.0293*	−0.0293*
					(0.016)	(0.016)	(0.016)	(0.016)
Leverage					0.0027	0.0021	0.0019	0.0017
					(0.013)	(0.012)	(0.012)	(0.012)
IVol					−0.0025	−0.0021	−0.0022	−0.0022
					(0.017)	(0.017)	(0.017)	(0.017)
MAX					−0.0013	−0.0020	−0.0027	−0.0033
					(0.026)	(0.026)	(0.026)	(0.026)
Coskewness					−0.0146	−0.0144	−0.0138	−0.0137
					(0.014)	(0.014)	(0.014)	(0.014)
Cokurtosis					0.0072	0.0077	0.0072	0.0071
					(0.013)	(0.013)	(0.013)	(0.013)
DBeta					−0.0281	−0.0289	−0.0289	−0.0289
					(0.022)	(0.021)	(0.021)	(0.021)
Vol-of-vol					−0.0051	−0.0050	−0.0050	−0.0053
					(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.0029	0.0034	0.0035	0.0037	0.0994	0.0999	0.1000	0.1000
t-statistic	[−1.868]	[−2.650]	[−2.756]	[−2.244]	[−2.358]	[−3.077]	[−3.119]	[−3.027]

A8 Alternative VAR Specifications

Table A13: Summary Statistics – Alternative VAR Specifications

This table presents summary statistics for (Panel A) and correlations among (Panel B) the $LR_{VAR(x)}$ measures using different VAR specifications. Mean is the time-series average of the cross-sectional average. Std., Skewness, and Kurtosis present the average cross-sectional standard deviation, skewness, and kurtosis, respectively. Min and Max report the time-series average of the minimum and maximum observation in the cross-section. 5%, 25%, Median, 75% and 95% indicate the averages of the corresponding cross-sectional quantiles, respectively. $LR^*_{VAR(x)}$ denotes the raw (non-standardized) $LR_{VAR(x)}$ measure. Panel B presents the average cross-sectional correlations of the respective variables. The sample period is January 1996 until December 2016.

Panel A: Summary Statistics:

	Mean	Std.	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
$LR^*_{VAR(1)}$	978	352	0.00	2.46	3.13	389	740	984	1,209	1,561	2,200
$LR^*_{VAR(5)}$	1,037	345	0.02	2.61	13.5	464	807	1,037	1,259	1,607	2,582
$LR^*_{VAR(22)}$	1,077	332	0.19	2.89	47.6	568	861	1,065	1,274	1,613	3,712
$LR^*_{HVAR(3)}$	873	341	0.17	2.95	−43.1	330	648	866	1,084	1,429	3,156

Panel B: Correlations:

	$LR_{VAR(1)}$	$LR_{VAR(5)}$	$LR_{VAR(22)}$	$LR_{HVAR(3)}$
$LR_{VAR(1)}$	*	0.98	0.85	0.92
$LR_{VAR(5)}$		*	0.90	0.96
$LR_{VAR(22)}$			*	0.96
$LR_{HVAR(3)}$				*

Table A14: Portfolio Sorts – VAR(5)

At the end of each month, we sort the stocks into five portfolios according to their $LR_{VAR(5)}$ using a VAR model with 5 lags. The column labeled Q1–Q5 refers to the hedge portfolio buying the quintile of stocks with the lowest $LR_{VAR(5)}$ and simultaneously selling the stocks in the quintile with the highest $LR_{VAR(5)}$. Panel A presents the results for equally weighted portfolio sorts while in Panel B we weigh the stocks in each portfolio according to their market value. We hold the portfolios for one month. The row labeled Average Return return denotes the average portfolio excess return. CAPM alpha, FF3 alpha, four-factor alpha, five-factor alpha, and FF5 alpha refer to the alphas of the CAPM, the Fama & French (1993) three-factor the Carhart (1997) four-factor model, the five-factor model (including Pástor & Stambaugh, 2003 liquidity), and the Fama & French (2015) five-factor model, respectively. Robust Newey & West (1987) standard errors using 5 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Panel A: Equally Weighted:						
Average Return	0.0958**	0.0935**	0.0815*	0.0727	0.0545	0.0413**
	(0.0423)	(0.0422)	(0.0436)	(0.0460)	(0.0508)	(0.0177)
CAPM alpha	0.0239	0.0198	0.0058	−0.0072	−0.0318**	0.0557***
	(0.0174)	(0.0163)	(0.0166)	(0.0150)	(0.0148)	(0.0151)
FF3 alpha	0.0107	0.0087	−0.0049	−0.0159	−0.0385***	0.0492***
	(0.0095)	(0.0096)	(0.0119)	(0.0131)	(0.0121)	(0.0127)
four-factor alpha	0.0084	0.0115	0.0013	−0.0063	−0.0275**	0.0359***
	(0.0104)	(0.0096)	(0.0112)	(0.0119)	(0.0114)	(0.0127)
five-factor alpha	0.0050	0.0061	−0.0041	−0.0115	−0.0311***	0.0361***
	(0.0103)	(0.0091)	(0.0112)	(0.0116)	(0.0113)	(0.0128)
FF5 alpha	0.0068	0.0012	−0.0103	−0.0187	−0.0280**	0.0348**
	(0.0099)	(0.0088)	(0.0110)	(0.0123)	(0.0124)	(0.0138)
Panel B: Value-Weighted:						
Average Return	0.0991***	0.0884**	0.0575	0.0683*	0.0580	0.0411**
	(0.0350)	(0.0355)	(0.0374)	(0.0403)	(0.0441)	(0.0190)
CAPM alpha	0.0370***	0.0236**	−0.0081	0.0003	−0.0134	0.0504***
	(0.0118)	(0.0109)	(0.0094)	(0.0089)	(0.0104)	(0.0179)
FF3 alpha	0.0297***	0.0224**	−0.0087	0.0012	−0.0108	0.0406***
	(0.0100)	(0.0109)	(0.0081)	(0.0084)	(0.0101)	(0.0151)
four-factor alpha	0.0229**	0.0210*	−0.0090	0.0016	−0.0114	0.0343**
	(0.0101)	(0.0112)	(0.0079)	(0.0087)	(0.0100)	(0.0154)
five-factor alpha	0.0199**	0.0154	−0.0124	−0.0024	−0.0124	0.0323**
	(0.0097)	(0.0108)	(0.0077)	(0.0089)	(0.0102)	(0.0155)
FF5 alpha	0.0225**	0.0111	−0.0149*	−0.0033	−0.0080	0.0305*
	(0.0112)	(0.0111)	(0.0078)	(0.0087)	(0.0104)	(0.0158)

Table A15: Fama–MacBeth Regressions – Alternative VAR Specifications

This table presents average coefficient estimates from monthly Fama & MacBeth (1973) regressions using $LR_{VAR(x)}$ derived from varying VAR models. Each month, we regress the excess stock returns over the next month on a constant, a $LR_{VAR(x)}$, as well as a series of control variables, all measured at the end of the current month. All right-hand-side variables are standardized to have zero mean and a volatility of one. In parentheses, we report robust Newey & West (1987) corrected standard errors using 5 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The row labeled t-statistic presents the t-statistic for the premium on $LR_{VAR(x)}$.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	0.0795*	0.0795*	0.0795*	0.0795*	0.0753	0.0769	0.0790	0.0784
	(0.044)	(0.044)	(0.044)	(0.044)	(0.061)	(0.061)	(0.061)	(0.061)
$LR_{VAR(1)}$	−0.0133**				−0.0125***			
	(0.006)				(0.004)			
$LR_{VAR(5)}$		−0.0121**				−0.0106***		
		(0.006)				(0.004)		
$LR_{VAR(22)}$			−0.0105				−0.0083**	
			(0.006)				(0.004)	
$LR_{HVAR(3)}$				−0.0103*				−0.0090**
				(0.006)				(0.004)
Beta					−0.0027	−0.0032	−0.0035	−0.0035
					(0.029)	(0.029)	(0.029)	(0.029)
Size					−0.0041	−0.0043	−0.0049*	−0.0047*
					(0.003)	(0.003)	(0.003)	(0.003)
Book-to-market					−0.0209	−0.0200	−0.0095	−0.0089
					(0.158)	(0.156)	(0.152)	(0.152)
BAS					0.0008	0.0040	0.0071	0.0057
					(0.034)	(0.034)	(0.034)	(0.034)
Momentum					0.0323*	0.0324*	0.0321*	0.0322*
					(0.018)	(0.018)	(0.018)	(0.018)
Short-term reversal					−0.0293*	−0.0293*	−0.0293*	−0.0293*
					(0.016)	(0.016)	(0.016)	(0.016)
Leverage					0.0017	0.0018	0.0019	0.0019
					(0.012)	(0.012)	(0.012)	(0.012)
IVol					−0.0022	−0.0021	−0.0024	−0.0022
					(0.017)	(0.017)	(0.017)	(0.017)
MAX					−0.0033	−0.0026	−0.0015	−0.0017
					(0.026)	(0.026)	(0.026)	(0.026)
Coskewness					−0.0137	−0.0137	−0.0139	−0.0139
					(0.014)	(0.014)	(0.014)	(0.014)
Cokurtosis					0.0071	0.0070	0.0074	0.0073
					(0.013)	(0.013)	(0.013)	(0.013)
DBeta					−0.0289	−0.0289	−0.0297	−0.0296
					(0.021)	(0.021)	(0.021)	(0.021)
Vol-of-vol					−0.0053	−0.0049	−0.0036	−0.0043
					(0.004)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.0037	0.0037	0.0036	0.0037	0.1000	0.0999	0.0998	0.0998
t-statistic	[−2.244]	[−2.003]	[−1.646]	[−1.686]	[−3.027]	[−2.674]	[−2.239]	[−2.409]