Good Volatility, Bad Volatility, and the Expected Stock Returns*

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Abstract

The volatility asymmetry can be captured by the relative difference of the good and bad semi-variance measures, termed relative signed jump variation. The volatility asymmetry risk disentangles the relationships between good/bad volatility, total volatility and cross-section/aggregate return at systemic level, and unifies the higher-moments anomalies at firm level. We show three novel results: (1) Based on cross-sectional sensitivities, volatility asymmetry risk, proxied by the relative signed jump extracted from 9 industry ETFs, is a significant priced risk factor with positive premium that is confounding with the negative premium of total volatility. (2) The stochastic discount factor and asset returns are asymmetrically dependent, and we propose a Asymmetric-DCAPM-SV model based on Bansal et al. (2013) with explicit solutions to show that the confounding relationship between volatility asymmetry and total volatility enters directly into the stochastic discount factor, thus need to be considered jointly and further helps explain equity premium. (3) Individual assets' relative signed jump variation significantly predict cross-sectional return (with spread as large as 23% annually), and is the driving force behind the higher moment anomalies in realized volatility, skewness and kurtosis.

JEL classification: C13, C14, G11, G12

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I. Introduction

The relation between risk and return is at the heart of asset pricing finance. This is perhaps most clearly evident in the simple ICAPM of Merton (1980), which directly relates the return on the market to its volatility. A long list of studies, including French et al. (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), and Bae et al. (2007), among many others, have sought to empirically investigate this simple relation between aggregate market return and volatility. These studies have emphasized the joint roles played by volatility "feedback" and "leverage" effects, whereby an increase (decrease) in volatility is associated with an increase (decrease) in future expected returns and lower (higher) contemporaneous returns, respectively. However, whereas the empirical support for the leverage effect is overwhelming, the positive relation between volatility and future expected returns has proven much more elusive empirically; see, e.g., the discussion in Bollerslev et al. (2012).[1] Meanwhile, studies by Ang et al. (2006), Adrian and Rosenberg (2008), Da and Schaumburg (2011) and Bansal et al. (2013), among others, have shown that aggregate market variance risk is indeed priced cross-sectionally, with changes in variance commanding a negative risk premium, thus implying that investors are willing to pay more for stocks that insure against future increases in volatility.[2]

Building on the classical ICAPM of Merton (1973), Campbell (1993, 1996) have forcefully argued that any variable that forecasts future market returns and/or volatility provides a natural candidate state variable for describing changes in the investor's opportunity set and in turn may help explain cross-sectional differences in the pricing of different assets.

More recently, the asymmetry in the volatility has been shown to presents strong predictability for future return and volatility. Patton and Sheppard (2013) and Nolte and Xu (2014) show that the realized variation stemming from past negative (positive) returns positively (negatively) predicts total aggregate market volatility. Breckenfelder and Tédongap (2012) show that the up (down) semi-variance positively (negatively) predicts future aggregate market returns, with the predictability the strongest over longer multi-month horizons. Guo et al. (2014) show that aggregate good and bad jump could predict oppositely the near term equity premiums. Moreover, using low frequency macro data and long-run risk framework of Bansal and Yaron (2004), Segal et al. (2013) show that imposing opposite signs on the coefficients of the good and bad economic uncertainty in the growth process indeed can generate opposite price among the size and momentum portfolios. We verify that the difference between the up and down semi-variance measures, corresponding to the signed

[1] Bandi and Perron (2008) and Bandi et al. (2013) have recently argued that the relationship between volatility end future expected returns is significant, but only over very long multi-year horizons.

[2] Consistent with these findings for the actual return variation, Conrad et al. (2013) find that stocks with high (low) options implied risk-neutral volatilities and covariances with the market similarly result in low (high) subsequent returns.

jump variation, results in the strongest predictability for both the returns *and* the volatility, thus naturally suggest the pricing ability of them.

To summarize the existing findings, we propose that the entangled theoretical and empirical results mentioned above naturally suggest that the relationships between good and bad semi-variances, future aggregate volatility, aggregate return and their cross-sectional prices, presents a self-consistent picture illustrated in the left panel of the following Figure 1. where $(\sigma^m_{t+1})^2$ represents

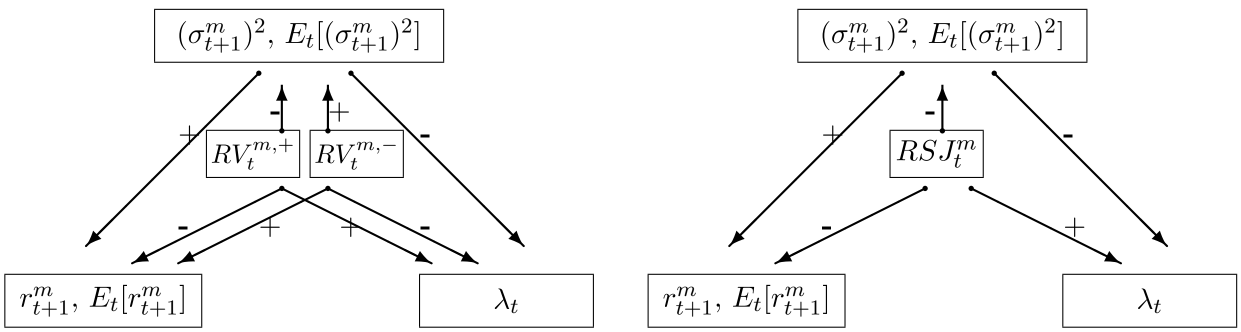

Figure 1. An Illustration of the effects of $RV_t^{m,+}$, $RV_t^{m,-}$, and RSJ_t^m

the future aggregate market variance, r^m_{t+1} represents the future aggregate market return and λ_t represent the cross-sectional premiums received by an asset's unit loading to the aggregate up and down semi-variances risks.

Moreover, from a different angle, studies on cross-sectional asset return have discovered higher-moments anomalies, where implied and realized higher moments of return have predictability for future return. Amaya et al. (2011) have documented that realized volatility, realized skewness, and realized kurtosis computed from individual assets' past return each have weak negative, strong negative, and weak positive return predictability in the cross-section, respectively. In the meanwhile, Conrad et al. (2013) show that higher moments extracted from option-implied densities also exhibit return predictability in the same direction. This constitutes a puzzle since the different directions of the return return predictability seem puzzling at first look.

Thus, our goal is to disentangle the seemingly puzzling relationships between total volatility, volatility asymmetry and return at two levels: the systematic risk level, and the individual return predictability level.

Set against this back ground, using high-frequency intraday data and newly developed econometric procedures based on Barndorff-Nielsen et al. (2010), we use the relative difference between realized good and bad semi-variance as measure of volatility asymmetry and term it Relative Signed Jump Variation. At the systematic level. We proxy the economy-wide volatility asymmetry risk using $ARSJ_t$, a value-weighted average of the signed jump variations from 9 industry exchange traded funds that together constitutes the S&P 500 Index. We investigate the cross-sectional pricing performance of volatility asymmetry risk in the presence of total volatility risk. From cross-sectional sensitivity, we show that volatility asymmetry risk, is a significant priced risk factor with positive premium that is confounding with the negative premium of total volatility. We prove that the stochastic discount factor and asset returns are asymmetrically dependent, and propose a Asymmetric-DCAPM-SV model based on Bansal et al. (2013) with explicit solutions to show that the confounding relationship between volatility asymmetry and total volatility enters directly into the stochastic discount factor, thus need to be considered jointly and further helps explain equity premium. At the individual return predictability level, individual relative signed jump variation significantly predict cross-sectional return (with spread as large as 23 % annually), and is the driving force behind the higher moment anomalies in realized volatility, skewness and kurtosis.

To our best knowledge, we are the first to provide evidence from firm sensitivity of volatility asymmetry risk as a risk based explanation. We are also the first to show that volatility asymmetry together has a confounding relationship with total volatility explicitly in the stochastic discount factor. We are also the first to document the economic large and statistically significant firm-level return predictability from relative signed jump variation.

The rest of the paper is organized as follows: Section II verify the relationships summarized in Figure 1 and present the data and high-frequency measures. Section III show that stochastic discount factor and asset return are conditionally asymmetrically dependent, and solves the complete Asymmetric-DCAPM-SV model and derive the bias for ignoring volatility asymmetry. Section IV presents the evidence that volatility asymmetry risk is a priced risk factor and estimates its factor premium. Section V presents the return predictability of individual assets' relative signed jump variation, and show that it drives the higher-moments anomalies. Section VI concludes.

II. High-Frequency Measure of Volatility Asymmetry

In this section we introduce the dataset together with the high-frequency variance measures used in this paper.

A. Data

A.1. TAQ data

The intraday high frequency data are constructed from the NYSE Trade and Quote (TAQ) dataset. The TAQ dataset contains all the listed equity securities from at least one of the three exchanges: NYSE, NASDAQ and AMEX. For each consolidate trade file, we obtain the second-by-second data set for the entire TAQ universe including 19896 unique individual equity assets and matched to the CRSP PERMNO number. We keep all the observations starting from 9:30 am to 4:00pm for a given trading day[3]. We used sample from 19930104 to 20131231, resulting in 5289 trading days, 1095 weeks and 252 months in the sample.

A.2. Low frequency data

For all daily frequency observations, we use several commonly used datasets. The Center for Research in Securities Prices (CRSP) database provides daily and monthly stock returns, number of shares outstanding, and daily and monthly trading volumes. We adjusted the stock returns for delisting to avoid survivorship bias.[4] We also use the stock distribution information from CRSP data to obtain the overnight return[5] The COMPUSTAT database provides accounting data such as book values. We obtain the daily and monthly Fama-French-Carhart four factor variables (Fama and French, 1993; Carhart, 1997) and portfolio test assets such as 25 size-B/M portfolios and 25 size-momentum portfolios from Kenneth R. French's data library.

B. Semi-Variances and Relative Signed Jump Variation

As shown by Barndorff-Nielsen et al. (2010), if an asset i's intraday log-price process follows a standard jump diffusion process:

$$p_\tau^i = \int_0^\tau \mu_s ds + \int_0^\tau \sigma_s dW_s + J_\tau \qquad (0 \leq \tau \leq 1) \tag{1}$$

[3]The cleaning rules are based on Barndorff-Nielsen et al. (2009). We supply the complete cleaning procedure in the Internet appendix

[4]When a stock is delisted, we use the delisting return as its return after its last trading day or month. In our sample, all delisting returns are available from CRSP.

[5]The high frequency TAQ data only contains the raw price without consideration of the price difference before and after distribution. We use the variable "Cumulative Factor to Adjust Price (CFACPR)" from CRSP to adjust the high-frequency overnight returns after a distribution.

the realized signed jump variation for asset i on day t only contains the difference in the jump variance

$$SJ_t^i = RV_t^{i,+} - RV_t^{i,-} \xrightarrow[n\to\infty]{p} \sum J_\tau^2 \mathbf{1}_{[J_\tau>0]} - \sum J_\tau^2 \mathbf{1}_{[J_\tau<0]} \tag{2}$$

where $\mu(\cdot)$ is a locally bounded predictable drift process, $\sigma(\cdot)$ is a strictly positive càdlàg process, $J(\cdot)$ is a pure jump process, $r_\tau^i = p_\tau^i - p_{\tau-\Delta_n}^i$ is the asset i's intra day return at time τ, sampled n times during the day, and $RV_t^{i,+}$, $RV_t^{i,-}$ are the positive and negative semi-variances:

$$RV_t^i = \sum (r_{\tau,t}^i)^2; \quad RV_t^{i,+} = \sum (r_{\tau,t}^i)^2 \mathbf{1}_{[r_{\tau,t}^i>0]}; \quad RV_t^{i,-} = \sum (r_{\tau,t}^i)^2 \mathbf{1}_{[r_{\tau,t}^i<0]}; \tag{3}$$

Alternatively, since Signed Jump captures only the tail variance differences, one can measure the jump variances by directly identifying the intraday price jumps, at the cost of more parametric assumption on the price processes. One popular parametric measure is the Threshold Jump Variation:

$$TJV_t^{i,+} = \sum (r_{\tau,t}^i)^2 \mathbf{1}_{[r_{\tau,t}^i>T_{\tau,t}^i]}; \quad TJV_t^{i,-} = \sum (r_{\tau,t}^i)^2 \mathbf{1}_{[r_{\tau,t}^i<T_{\tau,t}^i]}$$

$$TSJ_t^i = TJV_t^{i,+} - TJV_t^{i,-}; \tag{4}$$

where $T_{\tau,t}^i = \alpha\sqrt{\min\{RV_t^i, BV_t^i\}}\Delta_n^{\bar{\omega}} ToD_\tau^i$ is the instantaneous threshold, BV_t^i is the jump robust Bipower Variation of Barndorff-Nielsen and Shephard (2004), ToD_τ^i is the intraday instantaneous volatility pattern estimate, and $\alpha > 0, 0 < \bar{\omega} < 1/2$ are tuning parameters[6].

Since different assets may have different level of volatility, to obtain the relative difference of good and bad volatility, we divide the signed jump variation by the realized volatility to obtain the Relative Signed Jump Variation and the alternative measure Threshold Relative Signed Jump Variation for asset i on day t:

$$RSJ_t^i = \frac{SJ_t^i}{RV_t^i}; \qquad TRSJ_t^i = \frac{TSJ_t^i}{RV_t^i} \tag{5}$$

We verify that all results hold for the parametric measure, $TRSJ$.

We estimate the daily relative signed jump variation RSJ_t^i for every equity assets and aggregate to calendar week and month measures. As proxy for the economy-wide volatility asymmetry, we use the value-weighed average of the relative signed jump variation of the 9 industry exchange trade funds, which spans the S&P500 Index[7]

[6] In our calculation, $(\alpha, \bar{\omega}) = (3, 0.49)$. We verified that the results are robust to alternative choices of $(2, 0.45)$ and $(4, 0.49)$

[7] The 9 industry ETFs are XLY Consumer discretionary, XLP Consumer staples, XLE Energy, XLF Financial, XLV Health care, XLI Industrial, XLB Materials, XLK Technology, XLU Utilities. For our empirical analysis, the results are not sensitive to this choice of this set of ETFs

C. Volatility asymmetry and aggregate return and volatility

Before we present our theoretical and empirical results, we first verify in our data sample the documented relationships between good/bad volatility, aggregate return and volatility. To compare with the volatility predictability results of Patton and Sheppard (2013), we use the same HAR regressions

$$\begin{aligned} RV^m_{t+1,t+h} =& a_0 + a_1 RV^m_t + a_2 RV^{m,+}_t + a_3 RV^{m,-}_t + a_4 SJ^m_t \\ &+ b_1 RV^m_{t,W} + b_4 SJ^m_{t,W} \\ &+ c_1 RV^m_{t,M} + c_4 SJ^m_{t,M} + \varepsilon^p_{t+h} \end{aligned} \tag{6}$$

for the realized measures estimated on the SPDR ETF. Table II show the result for the 1-month ahead volatility prediction. Consistent with Patton and Sheppard (2013), the good and bad volatility have strong opposite predictability power to the future aggregate volatility, with the bad (good) volatility forcasting the increase (decrease) of future volatility. The signed jump variation therefore have significant negative predictability towards future volatility. To compare with the aggregate return predictability results of Breckenfelder and Tédongap (2012), we perform a non-overlapping monthly regression of aggregate return on the innovation in volatility measures:

$$r^m_{t+1,t+h} = a_0 + a_1 \Delta RV^m_{t-h+1,t} + a_2 \Delta RV^{m,+}_{t-h+1,t} + a_3 \Delta RV^{m,-}_{t-h+1,t} + a_4 \Delta SJ^m_{t-h+1,t} + \varepsilon^m_{t+h} \tag{7}$$

Table III reports the result of this regression. Consistent with Breckenfelder and Tédongap (2012), the innovations in good and bad realized semi-variance have opposite return predictability with bad (good) volatility positively (negatively) predict aggregate future market return. The signed jump variation therefore have significant negative return predictability.

By combining the predictability power of both good and bad realized semi-variances, the relative signed jump therefore have the relationship with aggregate volatility and return illustrated in the Figure 1 right panel.

The summary statistics for the series are presented in Table I:

III. Theoretical Framework

To illustrate the channel through which the asymmetry in the volatilities can move the asset prices, we provide a simple model where asymmetry risk together with volatility risk contribute to the stochastic discount factor, and therefore move asset prices. We show that volatility asymmetry, together with total volatility serve as one component in the stochastic discount factor. In particular, the volatility asymmetry term enters equally with the total volatility, illustrating how asymmetry and total volatility jointly determine the volatility component of the stochastic discount factor. Furthermore, we show that ignoring the volatility asymmetry can cause significant bias in the stochastic discount factor. Because of this confounding relationship between the total volatility and volatility asymmetry, an unexpected high innovation in total aggregate volatility is not necessarily indicating a bad state, if during the same period most volatility comes from the good news as oppose to the bad news. By the same token, an unexpected high innovation in total aggregate volatility accompanied with large proportion of bad volatility proxies a worse investment opportunity set compared with the one indicated with only aggregate total volatility alone.

We build this model upon the Dynamic-CAPM-SV model of Bansal et al. (2013), while relaxing the conditional joint log-normality assumption between the stochastic discount factor and return, to allow for non-symmetric dependence on the tails. We term this model Asymmetric-DCAPM-SV model. It differs from the original DCAPM-SV model only that the innovation in the Jensen's inequality adjustment not only include the revisions in the expectations of time-varying total volatility, but also the revisions in the expectation of the time-varying volatility asymmetry. We first present the full solution to Asymmetric-DCAPM-SV model, then we discuss the importance of the asymmetric dependence, as well as the magnitude of the bias from ignoring asymmetry in the asset's premium.

A. The Asymmetric-DCAPM-SV model for Volatility Asymmetry Risk

A.1. Preferences and the Stochastic Discount Factor:

Following Bansal et al. (2013), we assume the discrete-time specification of the endowment economy, with agent's preferences described by a Kreps and Porteus (1978) recursive utility function of Epstein and Zin (1989) and Weil (1989). The lifetime utility of the agent, U_t, satisfies:

$$U_t = \left[(1-\delta) C_t^{1-\frac{1}{\psi}} + \delta (\mathbb{E}_t U_{t+1}^{1-\gamma})^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{8}$$

where C_t is the aggregate consumption level, δ is the subjective discount factor, γ is the coefficient of relative risk aversion, and ψ is the inter-temporal elasticity of substitution (IES). Denote $\theta =$

$(1-\gamma)/(1-\frac{1}{\psi})$

As shown in Epstein and Zin (1989), the stochastic discount factor M_{t+1} can be written in terms of log consumption growth rate, $\Delta c_{t+1} = \log C_{t+1} - \log C_t$, and the log return to the consumption asset, $r_{c,t+1}$.

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1} \tag{9}$$

A.2. Euler Equation and Jensen's Inequality Adjustment

The standard Euler equation:

$$\mathbb{E}_t \left[M_{t+1} R_{t+1} \right] = 1 \tag{10}$$

gives the price of any asset in the economy, in particular, the consumption asset. Expressing the pricing equation for the consumption asset return, in logs:

$$\begin{aligned} \mathbb{E}_t \left[M_{t+1} R_{c,t+1} \right] &= \mathbb{E}_t \left[\exp\left(m_{t+1} + r_{c,t+1} \right) \right] \\ &= \exp \left\{ \mathbb{E}_t \left[m_{t+1} + r_{c,t+1} \right] + \boldsymbol{V}_t \right\} = 1 \end{aligned} \tag{11}$$

where $\boldsymbol{V}_t$ is the adjustment term for Jensen's inequality. Since $\mathbb{E}_t \left[\exp\left(m_{t+1} + r_{c,t+1} \right) \right]$ is the moment generating function of $(m_{t+1} + r_{c,t+1})$, $M_{m+r}(t)$ evaluated at $t = 1$ [8]. In general,

$$\boldsymbol{V}_t \left(m_{t+1}, r_{c,t+1} \right) = \frac{1}{2} Var_t(m_{t+1} + r_{c,t+1}) + \boldsymbol{A}_t(m_{t+1} + r_{c,t+1}) \tag{12}$$

$\boldsymbol{A}_t(\cdot)$ captures higher moment terms and is the difference between the correct Jensen's inequality adjustment and its approximation under joint-normality. If M_{t+1} and $R_{c,t+1}$ are jointly log-normal, then $\boldsymbol{A}_t = 0$. If the joint log-normality assumption is relaxed, for example, asymmetric dependence is allowed, $\boldsymbol{A}_t \neq 0$.

Combining equations (11) and (9), substitute out m_{t+1}, we have:

$$\mathbb{E}_t \Delta c_{t+1} = \psi \log \delta + \psi \mathbb{E}_t r_{c,t+1} - \frac{\psi - 1}{\gamma - 1} \boldsymbol{V}_t = 0 \tag{13}$$

A.3. The Budget Constraint

Log-linearization of the budget constraint

$$W_{t+1} = (W_t - C_t) R_{c,t+1} \tag{14}$$

[8] Moment generating function of a random variable may not exists, however, since the fundamental asset pricing equation dictates that $E(MR) = 1$, the moment generating function expansion exists and is well-defined

gives, in logs

$$r_{c,t+1} = \kappa_0 + wc_{t+1} - \frac{1}{\kappa_1} wc_t + \Delta c_{t+1} \tag{15}$$

where $wc_t = w_t - c_t$ is the log wealth-to-consumption ratio and κ_0, κ_1 are log-linearization constant with $0 < \kappa_1 < 1$

As shown in Bansal et al. (2013), the forward-looking solution of this recursive equation is

$$c_{t+1} - \mathbb{E}_t c_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=0}^{\infty} \kappa_1^j r_{c,t+j+1}\right) - (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \kappa_1^j \Delta c_{t+j+1}\right) \tag{16}$$

A.4. Solution for Stochastic Discount Factor

As shown by Bansal et al. (2013), combining (9), (13) and (16), the innovation to the stochastic discount factor is driven by immediate return news, $N_{R,t+1}$, future discount rate news, $N_{DR,t+1}$, and volatility news, $N_{\boldsymbol{V},t+1}$

$$m_{t+1} - \mathbb{E}_t m_{t+1} = -\gamma N_{R,t+1} + (1-\gamma) N_{DR,t+1} + N_{V,t+1} \tag{17}$$

where

$$\begin{aligned} N_{R,t+1} &\equiv r_{c,t+1} - \mathbb{E}_t r_{c,t+1} \\ N_{DR,t+1} &\equiv (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \kappa_1^j r_{c,t+j+1}\right) \\ N_{\boldsymbol{V},t+1} &\equiv (\mathbb{E}_{t+1} - \mathbb{E}_t)\left(\sum_{j=1}^{\infty} \kappa_1^j \boldsymbol{V}_{t+j}\right) \end{aligned}$$

The model solution shows that the market price for immediate return news is γ, and the market price of future discount rate news (notice the summation starts from $r_{c,t+2}$) is $\gamma - 1$, while the volatility news, $N_{\boldsymbol{V},t+1}$, which includes *both* total *and* symmetric volatility adjustments, receives a price of -1;

Given the solution for the stochastic discount factor, under the same simplifying assumptions imposed in Bansal et al. (2013) (homoskedasticity for $(N_{\boldsymbol{V},t+1}, N_{DR,t+1} + N_{R,t+1})$), and an additional joint normality[9] for $(N_{\boldsymbol{V},t+1}, N_{DR,t+1} + N_{R,t+1})$, the correct Jensen's adjustment in equation (12) can be shown as:

[9] Note, that $N_{\boldsymbol{V},t+1}$ is already the innovation in the 2nd or higher moments of (m, r), this assumption will only affect 4th and above moments approximation in the moment generating function expansion.

$$
\begin{aligned}
\boldsymbol{V}_t(m_{t+1}+r_{c,t+1}) =& \frac{1}{2}Var_t(m_{t+1}+r_{c,t+1}) + \boldsymbol{A}_t(m_{t+1}+r_{c,t+1}) \\
=& \left(\frac{1}{2}Var_t + \boldsymbol{A}_t\right)(m_{t+1}+r_{c,t+1}) \\
=& \left(\frac{1}{2}Var_t + \boldsymbol{A}_t\right)[(1-\gamma)N_{DR,t+1} + (1-\gamma)N_{R,t+1} + N_{V,t+1}] \\
=& const + \left(\frac{1}{2}Var_t + \boldsymbol{A}_t\right)(1-\gamma)(N_{DR,t+1}+N_{R,t+1}) \\
=& const + \left(\frac{1}{2}Var_t + \boldsymbol{A}_t\right)(1-\gamma)\left[(\mathbb{E}_{t+1}-\mathbb{E}_t)\left(\sum_{j=0}^{\infty}\kappa_1^j r_{c,t+j+1}\right)\right] \\
=& const + \frac{1}{2}(1-\gamma)^2 Var_t\left[(\mathbb{E}_{t+1}-\mathbb{E}_t)\left(\sum_{j=0}^{\infty}\kappa_1^j r_{c,t+j+1}\right)\right] \\
&+ \boldsymbol{A}_t\left[(1-\gamma)(\mathbb{E}_{t+1}-\mathbb{E}_t)\left(\sum_{j=0}^{\infty}\kappa_1^j r_{c,t+j+1}\right)\right] \\
=& const + \frac{1}{2}\xi^2(1-\gamma)^2 Var_t\left[r_{c,t+1}\right] + \boldsymbol{A}_t\left[\xi(1-\gamma)r_{c,t+1}\right]
\end{aligned} \tag{18}
$$

where last step arise when there is a single return factor in the temporal dimension, i.e. the discounted long-run return news is proportional to the immediate return news plus independent noise:

$$
N_{DR} + N_R = \xi N_R + \varepsilon \tag{19}
$$

In the following section, we show that, under the asymmetric dependence assumption

$$
\boldsymbol{A}_t\left[\xi(1-\gamma)r_{c,t+1}\right] = const + \phi\left[Var_t(r_{c,t+1}|r_{c,t+1}<\mu_{r,t}) - Var_t(r_{c,t+1}|r_{c,t+1}<\mu_{r,t})\right] \tag{20}
$$

where $\phi > 0$ is a constant.

Therefore equation (18) becomes

$$
\begin{aligned}
\boldsymbol{V}_t(m_{t+1}+r_{c,t+1}) =& const + \frac{1}{2}\xi^2(1-\gamma)^2 Var_t\left[r_{c,t+1}\right] \\
&+ \phi\left[Var_t(r_{c,t+1}|r_{c,t+1}<\mu_{r,t}) - Var_t(r_{c,t+1}|r_{c,t+1}<\mu_{r,t})\right] \\
=& const + \eta Var_t\left[r_{c,t+1}\right] + \phi\left[Var_t^{+}\left(r_{c,t+1}\right) - Var_t^{-}\left(r_{c,t+1}\right)\right]
\end{aligned} \tag{21}
$$

B. The Volatility Asymmetry

Here we discuss the need for asymmetric dependence, derive the explicit form of the volatility asymmetry risk[10], and illustrate the bias from ignoring asymmetry in the volatility.

B.1. Why Asymmetry Dependence Between m and r ?

Traditionally, for asset returns and other economic variables, linear covariance or correlation, which are symmetric, has been the measure of choice for dependence. In the DCAPM-SV model, Bansal et al. (2013) assume that the conditional distribution of the stochastic discount factor M_{t+1} and $R_{c,t+1}$ are jointly log-normal. Under this assumption, $\boldsymbol{A}_t = 0$, and the Jensen's inequality adjustment in equation (21) comes only from total volatility. Yet it has been empirically established that the dependence among the economic variables are inherently asymmetric. This is perhaps best illustrated in the many scenarios of the business cycle. For example, Ang and Chen (2002) documents that "correlations between U.S. stocks and the aggregate U.S. market are much greater for downside moves, especially for extreme downside moves, than for upside moves." During bad economic conditions, the unobserved stochastic discount factor is higher, reflecting that investors will put a higher value to a unit payoff during that time. Therefore, a measure of dependence conditional on a higher stochastic discount factor, should be stronger (regardless of positive or negative) than conditional on a lower stochastic discount factor:

$$|\psi_t(r^i_{t+1}, r^j_{t+1}, ...|m_{t+1} > \mu_{m,t})| \quad > \quad |\psi_t(r^i_{t+1}, r^j_{t+1}, ...|m_{t+1} < \mu_{m,t})|$$

for any assets $r^i, r^j, ...$ in the consumption bundle. Moreover, since the stochastic discount factor is a function of the assets returns in the consumption bundle, the conditional dependence between the stochastic discount factor $m_{t+1} = f(r^i_{t+1}, r^j_{t+1}, ...)$ and any consumption asset return r^i_{t+1} should also satisfy:

$$|\psi_t(m_{t+1}, r^i_{t+1}|m_{t+1} > \mu_{m,t})| \quad > \quad |\psi_t(m_{t+1}, r^i_{t+1}|m_{t+1} < \mu_{m,t})|$$

If linear correlation is used as a measure of dependence, then we should see stronger correlation when stochastic discount factor is high during bad economic times.

B.2. A Copula Approach

To incorporate the asymmetry property, without assuming explicitly the numerical values of different correlations, we impose a copula dependence structure, where the degree of asymmetry

[10] Detail steps of derivation are supplied in the appendix and the Internet appendix

depends on the copula. We show how the asymmetric dependence can generate significant mispricing from the pricing equation $\mathbb{E}(MR) = 1$ alone. To demonstrate analytically, we use the Clayton Copula, which belongs to the simple asymmetric Archimedean copula class:

$$C_\theta(u, v) = \max\left\{u^{-\theta} + v^{-\theta} - 1; 0\right\}^{-\frac{1}{\theta}} \tag{22}$$

where θ is the Clayton copula parameter.

By Sklar's theorem (Sklar, 1959), the joint cumulative distribution of $F_{m,r}(a, b) = \mathbb{P}\left[m < a, r < b\right]$ can be described by the marginal distributions:

$$F_{m,r}(a, b) = C_\theta \left\{F_m(a), F_r(b)\right\} \tag{23}$$

$$\begin{aligned}
\boldsymbol{A}_t &= const + \phi \left[Var_t(m_{t+1} + r_{c,t+1}|m_{t+1} > \mu_{m,t}) - Var_t(m_{t+1} + r_{c,t+1}|m_{t+1} < \mu_{m,t})\right] \\
&= const + \phi(1-\gamma)^2 \chi \left[Var_t(r_{c,t+1}|r_{c,t+1} < \mu_{r,t}) - Var_t(r_{c,t+1}|r_{c,t+1} > \mu_{r,t})\right]
\end{aligned}$$

where $\phi > 0$ is a constant that depends on the choice of asymmetric copula, $\mu_{m,t} = \mathbb{E}_t\left[m_{t+1}\right]$ is the conditional mean of the stochastic discount factor.

In our empirical investigation, we use value-weighted average of the relative signed jump variation of the 30 exchange traded fund, $ASJ_t = \sum_{i=1}^{30} w_t^i RSJ_t^i$ as proxy to $-\boldsymbol{A}_t$;

This copula specification has three main advantages: 1) the joint non-linear dependences between m and r are not affected by the specific assumptions on the marginal distributions. Hence, if a practitioner believes in different classes of distributions for m or r or both, the distributions could be easily accompanied. In the example that follows, for the ease of exposition and comparison with Bansal et al. (2013), we use the normal distributions for both m and r; 2) The copula dependence can be captured by the joint distributions without altering the variable's moments and covariance. This can be valuable when we investigate the bias from ignoring the asymmetry in terms of the pricing equation based on moments and covariances. 3) Also, in terms of equation (12) and (21), the copula asymmetry adjustment will affect $\boldsymbol{A}_t$ alone, and leave the normal approximation unchanged. This is especially important to illustrate that volatility asymmetry captured in $\boldsymbol{A}_t$ together with total volatility $Var_t(\Delta c_{t+1})$ jointly determines the volatility adjustment $\boldsymbol{V}_t$, thus cannot be ignored.

C. The Bias from Ignoring Volatility Asymmetry

To illustrate the need to adjust for the bias induced by the asymmetric volatility dependence, we investigate the magnitude of the bias under the exact pricing equation, Equation (10)

$$\mathbb{E}\left[M_{t+1}R_{t+1}\right] = \mathbb{E}_t\left[\exp\left(m_{t+1}+r_{t+1}\right)\right] =$$
$$\exp\left[\mathbb{E}_t\left[m_{t+1}+r_{t+1}\right] + \frac{1}{2}Var_t\left(m_{t+1}+r_{t+1}\right) + \mathbf{A_t}\right] = 1$$

The relationship could be rewritten to derive the expected asset return:

$$\begin{aligned} \mathbb{E}\left[m+r\right] + \frac{1}{2}Var(m+r) + \mathbf{A} &= 0 \\ E(m) + \frac{1}{2}Var(m) + E(r) + \frac{1}{2}Var(r) + Cov(m,r) + \mathbf{A} &= 0 \\ -r_f + \log E(R) + Cov(m,r) + \mathbf{A} &= 0 \end{aligned}$$

where we observe that $E(m) + \frac{1}{2}Var(m) = -r_f$, and $E(r) + \frac{1}{2}Var(r) = \log E(R)$. When the true date generating process exhibit asymmetric dependence between m and r, the asymmetric adjustment term $\mathbf{A}$ is not zero and cannot be ignored. We could then derive the bias, express in the magnitude of the total return, when the volatility asymmetry term $\mathbf{A}$ is ignored:

$$\begin{aligned} E(R) &= \exp(r_f - \mathbf{A} - Cov(m,r)) \\ Bias &= E(R) - \exp(r_f - Cov(m,r)) \\ &= E(R) - \exp(r_f - \rho_{m,r}\sigma_m\sigma_r) \end{aligned} \tag{24}$$

where $\rho_{m,r}$ is the linear correlation coefficient between the log stochastic discount factor m and the asset return r.

C.1. Monte-Carlo Simulation Strategy

To understand the magnitude of the Bias demonstrated in equation (24), under the realistic calibration. We follow the existing literature on the empirical studies on the stochastic discount factor.

IV. The Pricing of Volatility Asymmetry Risk

The stochastic discount factor incorporates investor's valuation on the risky payoff. As investor's perceived investment opportunities varies over time, an asset that pays high when investment opportunities worsen is preferred by the risk-averse investor, and requires a lower expected return for investors to hold because of the hedging benefit. Therefore, sensitivities to a risk factor which proxies the worsening (recovering) of investment opportunity set will receive negative (positive) price, or premium.

As demonstrated by the solution to the Asymmetric-DCAPM-SV model, news in the expectation of future volatility includes both total volatility, and volatility asymmetry, moreover, total volatility receives a price of -1 and volatility asymmetry risk, $-\mathbf{A}_t$, receives price of 1. As a result, assets that co-moves positively (negatively) with total volatility, it's return increase when volatility shoots up (down), should receive negative (positive) premium. Similarly, assets that co-moves positively (negatively) with volatility asymmetry risk $-\mathbf{A}_t$, which is proxied by average relative signed jump variation $ARSJ_t$, should receive positive (negative) premium. For the total volatility risk, Ang et al. (2006) shows that total volatility risk, proxied by the daily innovation in the CBOE option-implied volatility index, receive negative premium in the cross-section.

To demonstrate that the volatility asymmetry risk matters and is a priced systematic risk factor, we need to demonstrate a cross-sectional return pattern that could be explained by the sensitivity to the volatility asymmetry risk, especially in the presence of total volatility risk. Specifically, if the solution to the theoretical model proposed in Section III were correct, empirically, we should see that:

(1) Portfolios grouped by the firms sensitivity to the aggregate volatility asymmetry risk, β^i_{ARSJ} show a positive return predictability pattern, where higher β^i_{ARSJ} have higher expected return. The pattern should be robust to a variety of different characteristics.

(2) Due to the confounding relationship between total volatility and volatility asymmetry risk, the return predictability pattern shown above should not only hold, but also be more significant after controlling for total volatility risk.

(3) The pricing performance of total volatility risk should also be improved once controlled for volatility asymmetry risk.

(4) Not only β^i_{ARSJ} should show future return predictability, there needs to be contemporaneous relationship between factor loadings and average return. The portfolios sorted on β^i_{ARSJ} should have similar loadings to the ex-post factor mimicking portfolio, $FARSJ$ which were constructed to vary contemporaneously with volatility asymmetry risk.

(5) The volatility asymmetry risk $ARSJ$ and volatility asymmetry risk return factor $FARSJ$

should price the portfolios sorted on β^i_{ARSJ} and $\beta^i_{\Delta VXO}$, which were constructed to have enough spread in the loadings of volatility asymmetry risk.

(6) As a systematic priced risk factor, the volatility asymmetry risk $ARSJ$ should price other assets in the economy.

We address each of the items above

A. Portfolios Grouped by β^i_{VIX} and β^i_{RSJ}

A.1. Pre-formation Regression

To understand if stocks with different sensitivities to the innovations on volatility asymmetry risk (proxied by $ARSJ$) have different average returns, our first step is to obtain the sensitivity in a Pre-formation regression, following Ang et al. (2006)[11]:

$$r^{e,i}_t = \beta_0 + \beta^i_{MKT} MKT_t + \beta^i_{\Delta VXO} \Delta VXO_t + \beta^i_{\Delta ARSJ^m} \Delta ARSJ^m_t + \varepsilon^i_t \tag{25}$$

where $r^{e,i}_t$ is the excess return for stock i, on day t, $MKT_t, \Delta VXO_t, \Delta ARSJ^m_t$ are the aggregate market return, innovation in the total volatility index and innovation in volatility asymmetry risk (proxied by value-weighted average of relative Signed Jump Variation from 30 exchange traded funds that covers a variety of industry and sectors to capture the volatility asymmetry information in the economy) respectively. We follow the Ang et al. (2006) in using daily data with 1-month window (for stocks with more than 17 daily observations in a given month), to estimate the coefficients with a reasonable degree of precision without losing the time-varying conditional information by aggregating across long horizon. We obtain a 3-D matrix ($T \times N \times K$) of individual asset's loadings to different risks across time, where T is number of months, N is the number of individual assets and K is the number of risk factors.

Our interest is the return pattern indicated by $\beta^i_{ARSJ^m}$, while controlling for $\beta^i_{\Delta VXO}$. We show that the positive premium received by $\beta^i_{ARSJ^m}$ in both portfolio sorting as well as firm-level Fama and MacBeth (1973) regressions.

We perform double sorting to control for each other between $\beta^i_{\Delta VXO}$ and $\beta^i_{ARSJ^m}$. To sort stocks by $\beta^i_{ARSJ^m}$ controlling for $\beta^i_{\Delta VXO}$, first, at the beginning of each month, all stocks are first grouped into deciles based on the previous month's $\beta^i_{\Delta VXO}$. Second, within each decile, stock are again grouped into deciles based on the previous month's $\beta^i_{ARSJ^m}$. Third, returns corresponding to the current month are then equal weighted to form the each portfolio return on the 10×10 grid.

[11] The CBOE changed the methodology of its volatility index from 2004. The original index, named VXO uses a model dependent method and covers S& P 100 Index constituents, while the new index, named VIX, uses a model-free method and covers S& P 500 Index constituents. In Ang et al. (2006) article, the VXO was used, for comparison, we also use VXO. We also document the results using VIX, as robustness check

Finally, we average across the $\beta^i_{\Delta VXO}$ dimension, and result in 10 portfolios ranked in $\beta^i_{ARSJ^m}$, while maintaining an even mixture of the $\beta^i_{\Delta VXO}$.

Tables IV and IV present the results of portfolio sorted on $\beta^i_{\Delta VXO}$ and $\beta^i_{ARSJ^m}$

A.2. Firm-level Fama-MacBeth Regression on Factor Loadings

While tables IV and IV concisely show that the return predictability of loadings on volatility asymmetry risk is robust (and is even improved) when controlling for loadings on total volatility risk, it is however insufficient as to the double-sorting (or triple sorting) methodology can only control for one or two characteristics at a time due to the limited number of individual assets (for example, a 10×10 sort require dividing the sample into 100 groups). To control for a variety of firm characteristics at a time, properly, we perform the firm-level Fama and MacBeth (1973) regressions on factor loadings and a variety of other characteristics. For every month t, we estimate the following cross-sectional regression:

$$r^i_{t+1} = \gamma_{0,t} + \gamma_{1,t}\beta^i_{ARSJ,t} + \gamma_{2,t}\beta^i_{\Delta VXO,t} + \phi'_t Z^i_t + \varepsilon^t_{t+1} \tag{26}$$

where r^i_{t+1} is the month $t+1$ return (in percentage) of the ith stock, and Z^i_t is a vector of characteristics and control variables for ith stock observed at the end of period t. The characteristics and control variables include log firm size, book-to-market, and idiosyncratic volatility, β_{MKT} from the pre-formation regression in equation (25). We report the results in table VI.

Table VI reports the results under various specifications.

A.3. Factor-Mimicking Portfolios

Following Breeden et al. (1989) and Lamont (2001), we create the maximum correlation mimicking return factor, $FARSJ$ to track innovations in $ARSJ$ by estimating the coefficient b in the following time-series regression:

$$\Delta ARSJ_t = c + b' X_t + u_t \tag{27}$$

where X_t is the return on the base asset, which were set to the $10\beta^i_{\Delta VXO} \times 10\beta^i_{ARSJ^m}$ portfolios, and by construction have different sensitivities to innovation in the volatility asymmetry risk. The return portfolio, $b'X_t$, is the factor $FARSJ$ that mimics innovation in the volatility asymmetry risk.

Table **??** shows the $\beta^i_{ARSJ^m}$ portfolios ex-post loading on the factor $FARSJ$.

B. The Premium of Volatility Asymmetry Risk

In the previous section we show that past sensitivities to the volatility asymmetry risk generates positive future average return in the presence of total volatility risk, and is consistent with the theoretical model Asymmetric-DCAPM-SV model. Moreover, the pre-formation $\beta^i_{ARSJ^m}$ portfolios demonstrate same pattern of post-formation loadings on the mimicking factor $FARSJ$. This shows that the volatility asymmetry risk is a priced risk factor, we can then estimate the factor premium of volatility asymmetry risk.

B.1. Fama-MacBeth Factor Price Estimation

Since $ARSJ$ is not asset return, the coefficients on the β_{ARSJ} cannot be interpreted as factor premiums, to estimate the factor premium, we use the mimicking factor $FARSJ$, which is the return of a portfolio. To estimate the factor premium λ_{FARSJ}, we use the $10\beta^i_{\Delta VXO} \times 10\beta^i_{ARSJ^m}$ pre-formation portfolios obtained through the pre-formation regression (25). This portfolio, by construction provide sufficient dispersion in the loadings of $FARSJ$ so that the cross-sectional regression could have reasonable power[12] We follow the portfolio level two-step procedure of Fama and MacBeth (1973). In the first stage, we estimate both full sample beta and 5-year rolling window beta in a time-series regression. In the second stage, we estimate the cross-sectional regression of portfolio's return on the loadings. For the full sample beta, the first stage regression is:

$$
\begin{aligned}
r^i_t =& \alpha^i_t + \beta^i_{MKT} MKT_t + \beta^i_{\Delta VIX} FVIX + \beta^i_{ARSJ} FARSJ \\
& + \beta^i_{SMB} SMB_t + \beta^i_{HML} HML_t + \beta^i_{LTR} LTR_t + \beta^i_{MOM} MOM_t + \beta^i_{STR} STR_t + \varepsilon^i_t
\end{aligned}
$$

And second stage follows:

$$
\begin{aligned}
\bar{r}^i =& \lambda_0 + \lambda_{MKT} \hat{\beta}^i_{MKT} + \lambda_{\Delta VIX} \hat{\beta}^i_{FVIX} + \lambda_{ARSJ} \beta^i_{ARSJ} \\
& + \lambda_{SMB} \hat{\beta}^i_{SMB} + \lambda_{HML} \hat{\beta}^i_{HML} + \lambda_{LTR} \beta^i_{LTR} + \lambda_{MOM} \beta^i_{MOM} + \lambda_{STR} \beta^i_{STR} + \epsilon^i
\end{aligned}
$$

where $MKT, SMB, HML, LTR, MOM, STR$ are the market factor, small-minus-big factor, high-minus-low factor, long-term reversal factor (winner minus loser on past 13 to 60 months), momentum factor (winner minus loser on past 2 to 12 months), short-term reversal factor (winner minus loser on past 1 month). For the full sample beta, the standard error are adjusted for error-in-variables problem according to Shanken (1992)

Similarly, for the rolling window beta, the first stage regression is estimated with 5 year rolling

[12]In Ang et al. (2006), the base assets is chosen to be portfolios sorted on β_{MKT} and $\beta_{\Delta VIX}$, for the same reason.

window:

$$
\begin{aligned}
r_t^i =& \alpha_t^i + \beta^i_{MKT,t} MKT_t + \beta^i_{\Delta VIX,t} FVIX + \beta^i_{ARSJ,t} FARSJ \\
&+ \beta^i_{SMB,t} SMB_t + \beta^i_{HML,t} HML_t + \beta^i_{LTR,t} LTR_t + \beta^i_{MOM,t} MOM_t + \beta^i_{STR,t} STR_t + \varepsilon^i_t
\end{aligned}
$$

The second stage is a predictive cross-sectional regression:

$$
\begin{aligned}
r_{t+1}^i =& \lambda_{0,t} + \lambda_{MKT,t} \hat{\beta}^i_{MKT,t} + \lambda_{\Delta VIX,t} \hat{\beta}^i_{FVIX,t} + \lambda_{ARSJ,t} \beta^i_{ARSJ,t} \\
&+ \lambda_{SMB,t} \hat{\beta}^i_{SMB,t} + \lambda_{HML,t} \hat{\beta}^i_{HML,t} + \lambda_{LTR,t} \beta^i_{LTR,t} + \lambda_{MOM,t} \beta^i_{MOM,t} + \lambda_{STR,t} \beta^i_{STR,t} + \epsilon^i
\end{aligned}
$$

The factor premium and the standard error are obtained as $\hat{\gamma}_f = \frac{1}{T} \sum \hat{\gamma}_{f,t}$, $\hat{\sigma}^2_{\hat{\gamma}_f} = \frac{1}{T-1} \sum (\hat{\gamma}_{f,t} - \hat{\gamma}_f)^2$

Table XI reports the result for both full sample beta and rolling window beta.

B.2. Other Test Assets

The base asset $10\beta^i_{\Delta VXO} \times 10\beta^i_{ARSJ^m}$ portfolios are by construction have a large dispersion in the sensitivities to total volatility risk and volatility asymmetry risk. However, in our Asymmetric-DCAPM-SV model, the volatility asymmetry risk, together with total volatility risk contribute to a significant part of the stochastic discount factor. Hence the pricing performance of such a systematic risk factor should not be limited to only a specifically formed portfolios. To demonstrate the pricing power of volatility asymmetry risk, we also perform the Fama-MacBeth regression on alternative test assets, including the 25 size-B/M portfolios and 25 size-momentum portfolios.

The results for alternative test assets are reported in tables XII, XIII XIV, and show that the volatility asymmetry risk is indeed able to price a large selection of assets.

C. Robustness Checks

V. Return Predictability Based on Individual Firm's RSJ^i

We find that individual firm's past month relative Signed Jump variation RSJ^i has strong predictability for that firm's next month return. The monthly rebalanced long-short portfolio earn an average spread of xxx per month. The predictability coming from RSJ^i unifies the documented higher moments anomalies. Specifically, we show that portfolios grouped by RSJ^i drives the pattern of portfolios grouped by realized skewness documented in Amaya et al. (2011), and by controlling for RSJ^i, the predictability of realized volatility, realized skewness, and realized kurtosis disappear. The puzzling directions of the predictability of the higher moments can be unified by the direction and the magnitude of the predictability of RSJ^i. We also show that the portfolios grouped by past RSJ^i is robust after controlling for 1-month short-term reversal. We present the analysis using both the intuitive portfolio sorts as well as the firm-level Fama and MacBeth (1973) cross-sectional regressions. Recent development on intraday event studies (Boudt and Petitjean, 2014), among others, suggest that news flow causes jumps in intraday prices. Since limiting theory shows that RSJ^i directly captures the differences in the jump variations on the two tails, we do not prove, but suggest a potential explanation: Good and bad unobserved information arrival result in high-frequency jump in the stock prices. By directly measuring the relative magnitude of the positive and negative jump variances, the RSJ^i can better capture the return impact of the news than the other higher moment measures (namely, the realized volatility, realized skewness and realized kurtosis).

A. The Higher Moments Anomalies

Recent studies have investigated future return predictability coming from the past period higher moments, and found puzzling results. For the second moment, Ang et al. (2006) using daily data have documented that stocks grouped by return volatility as well as the idiosyncratic volatility relative to the Fama and French (1993) model, presents negative return predictability, i.e. high volatility low future return. While Bali and Cakici (2008); Fu (2009) among others have found opposite result using different data period and methodology. Using high-frequency data from 1997-2008,(Amaya et al., 2011) have found that realized volatility have insignificant negative predictability power, while realized kurtosis have borderline positive predictability power. Moreover, Amaya et al. (2011) have shown that past week realized skewness constructed from high frequency intraday data negatively predict next week's return. Using option data to extract the ex-ante option-implied moments, Conrad et al. (2013) found predictability results in similar directions compared to Amaya et al. (2011).

A more detailed look, the "hard-to-understand" directions of the predictability from various moments seem to suggest that different components of the return have different predictability. Empirically, the predictability differs in two important ways: the magnitude of the increments, and the sign of the increments. By construction, realized kurtosis differs from the realized volatility only by raising the increments to a higher power, thus putting more weights on the larger increments and more penalty to the smaller increments. The difference in return predictability between realized volatility and realized kurtosis suggests that the jumps or larger increments possess different predictability power compared to the diffusive or smaller increments. In addition to the magnitudes of the increments, the signs of the increments are also suggested to matter for the direction of predictability. In particular, since skewness can be viewed as the third power of positive increments minus the third power of negative increments, the negative predictability from skewness suggest that positive price increments predict lower future return, while negative price increments predict higher future return.

Prior to any further empirical investigation, if the above interpretation of the existing results were correct, by separating the positive and negative, as well as the large and small price increments, the RSJ^i should show the following return predictability property: (1) Higher RSJ^i should predict lower future return, since it takes the difference of positive and negative jump variations; (2) Portfolios sorted on RSJ^i should have larger spread than the ones sorted on other higher moments, since in the limit, RSJ^i only measures the large jumps, and is independent from the small price increments (which is suggested to differ from large price increments); (3) Once controlled for RSJ^i, the original directions of the predictability from other higher moments should disappear, since the other higher moments measures the driving functional form indirectly.

Using the novel large cross-section and long time-span high-frequency data from TAQ covering 19896 stocks and from 1993 to 2013. We show that all three of the above property are verified. We first verify the return patterns by forming equal-weighted [13] portfolios based on past period firm characteristics, and look at the average future period return. Specifically:

(1) We observe a very monotonic return pattern on portfolios sorted on RSJ^i, with higher past RSJ^i decile predicting lower future return; Table VII reports the decile portfolios grouped by previous week and month RSJ^i. The average next month (week) return varies strictly monotonically from 1.515% (0.506%) for the lowest decile to 0.967% (0.079%) for the highest decile. Figure **??** graphically demonstrate this strict monotonic pattern.

(2) The monthly (weekly) re-balancing long-short portfolio have a premium of -0.548% (-0.427%), and significant robust t-statistics of -3.82 (-14.74), which corresponds to -6.6% (-22.2%) return annually. This spread is significantly larger than the spread obtained from sorting on other realized higher moments. Table VIII reports the result from sorting on realized variance,

[13] The results for the market-capital weighted portfolios are similar and we also provide them in the appendix

realized skewness and realized volatility.

(3) We show that portfolios double-sorted on RSJ^i controlling for other higher moments (realized skewness, realized kurtosis and realized volatility) retain the statistically significant spread and monotonic pattern, while portfolios double-sorted on other higher moments controlling for RSJ^i, shows insignificant spread or even reverse pattern compared to the uncontrolled single sorted portfolios. Table VIII reports the double-sort comparison between RSJ^i and other higher moments.

The above cross-sectional return predictability of RSJ^i can also be confirmed using a firm-level Fama and MacBeth (1973) cross-sectional regression, controlling for all characteristics together. For every period t, we estimate the following cross-sectional regression:

$$r_{t+1}^i = \gamma_{0,t} + \gamma_{1,t} RSJ_t^i + \phi_t' Z_t^i + \varepsilon_{t+1}^t \tag{28}$$

where r_{t+1}^i is the period $t+1$ return (in percentage) of the ith stock, and Z_t^i is a vector of characteristics and control variables for ith stock observed at the end of period t. The characteristics and control variables include log firm size, book-to-market, lagged return, realized volatility, realized skewness and realized kurtosis. We report the results in table IX. For all the specifications, the coefficients for RSJ^i is significantly negative, consistent with the portfolio sorting result that high RSJ^i predicts lower future return. When controlling for RSJ^i, the predictability from other higher moments disappears, while the coefficient of RSJ^i remains significant.

B. The Past Return, RSJ^i, and Price Paths

It is worth noting that the Relative Signed Jump Variation, RSJ^i, provides incremental predictability beyond the past cumulative return, indicating that even when the end-points of prices are the same, the intra-day price path matters, and in particular, the intra-day jump variations provide valuable information for future return. Table VIII, panel B, and C shows that the future return predictability of RSJ^i remains economically and statistically significant after controlling for past return, with a spread of 0.302% per month and robust t-statistics of 2.72. At the same time the significance of past return's predictability drops once controlled for RSJ^i. Table IX also indicate that the predictability RSJ remain significant after controlling for all moments of return for the same period, where past return can be viewed as the $1st$ moment. The two variables have positive correlations in the sense that if a stock has larger and more number of positive jumps than negative jumps, the cumulative return for that stock that period should be high, yet they could be capturing different characteristics. By construction, RSJ^i is constructed using the high-frequency intra-day return, and measures directly the relative difference between positive jump variations and negative jump variations, thus paying attention to and summarizing the intra-day characteristics of the price path. On the other hand, the past 1-month cumulative return, ignores the intra-day price paths, and only captures the end-points.

Relating to the recent studies in news and price jumps, the incremental predictability of RSJ beyond the cumulative return suggest that RSJ could be summarizing the news information for the period estimated, thus important for future return predictability. Using DJIA stocks, Boudt and Petitjean (2014) found that firm-specific news could drive the occurrence of price jumps. Although we do not attempt to prove the links between unobserved information flow, observed news release and price jumps, the predictability of RSJ^i suggest that information useful for return predictability could be embedded in the intra-day price path, and information extracted from jumps clearly stands out.

VI. Conclusion

To conclude, we verify the literature's documentation on the return, total volatility predictability around good and bad volatilities. We present evidence on firm loadings to support that volatility asymmetry risk is an important risk factor, and have strong pricing power to various different assets. We also develop an Asymmetric-DCAPM-SV model with explicit solution to the stochastic discount factor that demonstrate a confounding relationship between volatility asymmetry risk and the total volatility risk. Because of the confounding relationship, the pricing power of total volatility and is improved when controlled for volatility asymmetry. We show that the pricing performance of volatility asymmetry risk is robust to a large variety of characteristics and controls. At the firm-level, we verify the higher-moments anomalies in future return predictability, and show that relative signed jump variations is the driving force behind the seemingly puzzling directions of return predictabilities, and we point the the recent advance in the event studies to suggest that a potential explanation is that equity prices serve as directional information exchange between participants in the market, and relative signed jump variation better summarizes the information in the price-paths embedded only in the large intraday price increments, which are driven by the flow of information. Prove or disprove this conjecture requires resolution to the challenge imposed by the unobserved information flow, and can be of interest to further study.

Table I
Summary Statistics

This table reports the summary statistics at daily frequency. The columns are: SPY return, SPY realized variance, CBOE VIX, CBOE VXO, SPY Signed Jump Variation, SPY Threshold Signed Jump Variation, SPY Relative Signed Jump Variation, SPY Relative Threshold Signed Jump Variation, SPY Realized Skewness, SPY Realized Kurtosis, Average Signed Jump Variation of 9 Industry ETFs, Average Relative Signed Jump Variation of 9 Industry ETFs, respectively. Top panel covers all the trading days from 1993 to 2013, the bottom panel covers all trading days from 1999 to 2013, during which the 9 Industry ETFs become available. The daily return data are obtained from CRSP(Center for Research in Stock Prices) database. The high frequency variance measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

Whole Sample 1993-2013

	r_t^m	RV_t^m	VIX_t	VXO_t	SJ_t^m	TSJ_t^m	RSJ_t^m	$RTSJ_t^m$	$RSkew_t^m$	$RKurt_t^m$	ASJ_t	$ARSJ_t$
Mean	0.042	1.559	20.387	20.937	-0.025	0.009	0.036	-0.007	0.205	10.361	—	—
Std.Dev.	1.217	3.444	8.424	9.247	1.903	0.606	0.358	0.163	2.012	10.403	—	—
Autocorr(1)	-0.067	0.503	0.979	0.975	-0.033	-0.042	-0.038	-0.009	-0.031	0.066	-0.009	-0.035
Corr.												
r_t^m	1.000	—	—	—	—	—	—	—	—	—	—	—
RV_t^m	-0.078	1.000	—	—	—	—	—	—	—	—	—	—
VIX_t	-0.114	0.592	1.000	—	—	—	—	—	—	—	—	—
VXO_t	-0.121	0.594	0.983	1.000	—	—	—	—	—	—	—	—
SJ_t^m	0.506	-0.404	-0.113	-0.112	1.000	—	—	—	—	—	—	—
TSJ_t^m	0.198	0.344	0.068	0.076	0.143	1.000	—	—	—	—	—	—
RSJ_t^m	0.688	-0.066	-0.097	-0.100	0.391	0.127	1.000	—	—	—	—	—
$RTSJ_t^m$	0.285	0.034	0.001	0.004	0.089	0.329	0.439	1.000	—	—	—	—
$RSkew_t^m$	0.542	-0.067	-0.073	-0.076	0.430	0.095	0.933	0.312	1.000	—	—	—
$RKurt_t^m$	0.125	0.168	-0.040	-0.059	0.020	0.052	0.165	0.018	0.205	1.000	—	—
ASJ_t	—	—	—	—	—	—	—	—	—	—	—	—
$ARSJ_t$	—	—	—	—	—	—	—	—	—	—	—	—

Industry ETFs Available Sample 1999-2013

	r_t^m	RV_t^m	VIX_t	VXO_t	SJ_t^m	TSJ_t^m	RSJ_t^m	$RTSJ_t^m$	$RSkew_t^m$	$RKurt_t^m$	ASJ_t	$ARSJ_t$
Mean	0.026	1.686	21.624	22.216	-0.037	0.012	0.029	-0.008	0.178	9.904	-0.027	0.020
Std.Dev.	1.309	3.826	8.863	9.823	2.183	0.647	0.360	0.128	2.033	10.754	2.450	0.269
Autocorr(1)	-0.065	0.507	0.981	0.977	-0.036	-0.028	-0.059	-0.011	-0.049	0.006	-0.009	-0.036
Corr.												
r_t^m	1.000	—	—	—	—	—	—	—	—	—	—	—
RV_t^m	-0.080	1.000	—	—	—	—	—	—	—	—	—	—
VIX_t	-0.121	0.600	1.000	—	—	—	—	—	—	—	—	—
VXO_t	-0.128	0.599	0.986	1.000	—	—	—	—	—	—	—	—
SJ_t^m	0.503	-0.431	-0.124	-0.121	1.000	—	—	—	—	—	—	—
TSJ_t^m	0.155	0.367	0.076	0.086	0.102	1.000	—	—	—	—	—	—
RSJ_t^m	0.716	-0.062	-0.105	-0.110	0.398	0.106	1.000	—	—	—	—	—
$RTSJ_t^m$	0.276	0.051	0.015	0.019	0.089	0.362	0.345	1.000	—	—	—	—
$RSkew_t^m$	0.567	-0.067	-0.083	-0.087	0.441	0.074	0.929	0.209	1.000	—	—	—
$RKurt_t^m$	0.134	0.203	0.038	0.015	0.013	0.048	0.184	0.032	0.229	1.000	—	—
ASJ_t	0.563	-0.325	-0.110	-0.109	0.925	0.082	0.435	0.076	0.467	0.058	1.000	—
$ARSJ_t$	0.719	-0.075	-0.114	-0.119	0.394	0.078	0.923	0.252	0.867	0.186	0.466	1.000

Table II
Volatility Asymmetry in Forecasting Aggregate Volatiltiy

This table reports the HAR regression specified in equation (6), according to Patton and Sheppard (2013), at the monthly level, for the SPDR ETF. Data covers all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks and 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database, and the weekly returns are compounded from daily holding period return within that week. The Relative Signed Jump measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

$RV^m_{t+1\to h}$	RV^m_t	$RV^{m,+}_t$	$RV^{m,-}_t$	SJ^m_t	$RV^m_{t,w}$	$SJ^m_{t,w}$	$RV^m_{t,m}$	$SJ^m_{t,m}$	R^2
h=22	0.091				0.293		0.325		0.544
	(4.68)				(3.13)		(4.12)		
		-0.127	0.404		0.271		0.314		0.557
		(-3.27)	(4.19)		(3.04)		(3.93)		
	0.139			-0.265	0.271		0.314		0.557
	(4.03)			(-4.09)	(3.04)		(3.93)		
	0.101			-0.132	0.343	-0.724	0.305		0.569
	(4.34)			(-3.43)	(2.94)	(-2.60)	(3.52)		
	0.101			-0.129	0.327	-0.642	0.333	-0.429	0.569
	(4.35)			(-3.27)	(2.30)	(-1.62)	(2.65)	(-0.57)	

Table III
Volatility Asymmetry in Forecasting Aggregate Return

This table reports the monthly non-overlapping simple OLS regression specified in equation (7), for the SPDR ETF. Data covers all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks and 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database, and the weekly returns are compounded from daily holding period return within that week. The Relative Signed Jump measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

$r^m_{t+1\to h}$	$\Delta RV^m_{h\to t}$	$\Delta RV^{m,+}_{h\to t}$	$\Delta RV^{m,-}_{h\to t}$	$\Delta SJ^m_{h\to t}$	R^2
h=22	0.019				0.005
	(2.30)				
		0.029			0.002
		(1.70)			
			0.046		0.008
			(2.92)		
				-0.224	0.010
				(-1.92)	
		-0.290	0.356		0.025
		(-2.16)	(2.48)		
	0.033			-0.323	0.025
	(4.25)			(-2.33)	

Table IV
Portfolios Grouped by $\beta^i_{ASJ,t}$ and $\beta^i_{VXO,t}$, Whole Sample: 1998-2013

This table reports the quintile portfolios grouped by the individual asset's sensitivities of volatility asymmetry risk $\beta^i_{ASJ,t}$, and total volatility risk $\beta^i_{VXO,t}$, estimated by the pre-formation regression according to equation (25). At the beginning of month t, all stocks are grouped into deciles based on the previous period's sensitivities, returns corresponding to the period from month t to $t+1$ (predictive) are then averaged to form the portfolio return. The Returns are reported in percentage, and averaged across time. Each column named from 1 to 5 corresponds to the deciles from Low to High on the sorted characteristics. The column named "5-1" corresponds to the Long-Short portfolio of buying the highest and selling the lowest decile portfolios. Panel A reports the portfolios sorted on $\beta^i_{ASJ,t}$. Panel B reports the double sort first in $\beta^i_{VXO,t}$, then $\beta^i_{ASJ,t}$, then pooled across $\beta^i_{VXO,t}$ quintiles. Panel C and D reports the portfolios sorted on $\beta^i_{VXO,t}$. The robust t-statistics are reported in square brackets below the mean return, and are adjusted for Newey and West (1987) standard error with 12 lags (corresponding to 1-year). The rows named $\log(size^i)$ reports the average logarithm of the firm size; The rows named $\beta^i_{ASJ,t}$ and $\beta^i_{VXO,t}$ are the average sensitivities of the firm within each portfolios; The rows named nFirms are the average number of firms in each portfolio. Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19980101 to 20131231, covering 9:30am to 4:00pm, resulting in a total of 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database.

Decile	5-1	1	2	3	4	5
A: Single Sorted on $\beta^i_{ASJ,t}$, Monthly, 199801-201312						
$r_{t+1}(\%)$ (value weight)	0.615	0.570	0.652	0.681	0.871	1.185
	[2.04]	[1.82]	[2.83]	[2.93]	[2.64]	[2.83]
$r_{t+1}(\%)$ (equal weight)	0.384	0.576	0.703	0.740	0.827	0.960
	[1.95]	[1.49]	[2.46]	[2.43]	[2.33]	[1.99]
$\log(size^i)$		8.310	8.849	8.972	8.983	8.586
$\beta^i_{ASJ,t}$		-1.279	-0.056	0.371	0.846	2.211
nFirms		890.714	891.389	891.425	891.389	890.714
B: Double Sorted on $\beta^i_{ASJ,t}$, controlling for $\beta^i_{VXO,t}$, Monthly, 199801-201312						
$r_{t+1}(\%)$ (value weight)	0.539	0.667	0.646	0.750	0.843	1.206
	[2.05]	[2.76]	[2.76]	[2.95]	[2.87]	[3.01]
$r_{t+1}(\%)$ (equal weight)	0.401	0.551	0.699	0.765	0.841	0.951
	[1.87]	[1.68]	[2.39]	[2.51]	[2.45]	[2.24]
$\log(size^i)$		8.225	8.771	8.929	8.994	8.789
$\beta^i_{VXO,t}$		-0.352	-0.272	-0.234	-0.201	-0.110
$\beta^i_{ASJ,t}$		-1.014	-0.053	0.378	0.840	1.943
nFirms		177.551	178.208	178.220	178.208	177.551
C: Single Sorted on $\beta^i_{VXO,t}$, Monthly, 199801-201312						
$r_{t+1}(\%)$ (value weight)	0.280	0.783	0.734	0.707	0.733	1.063
	[0.94]	[1.85]	[2.59]	[2.81]	[2.90]	[3.19]
$r_{t+1}(\%)$ (equal weight)	0.112	0.745	0.737	0.751	0.718	0.857
	[0.72]	[1.58]	[2.13]	[2.46]	[2.48]	[2.18]
$\log(size^i)$		8.723	9.098	9.000	8.747	8.131
$\beta^i_{VXO,t}$		-1.119	-0.452	-0.210	0.006	0.607
nFirms		890.714	891.389	891.425	891.389	890.714
D: Double Sorted on $\beta^i_{VXO,t}$, controlling for $\beta^i_{ASJ,t}$, Monthly, 199801-201312						
$r_{t+1}(\%)$ (value weight)	-0.131	0.939	0.808	0.749	0.724	0.808
	[-0.54]	[2.52]	[2.89]	[3.14]	[2.87]	[2.74]
$r_{t+1}(\%)$ (equal weight)	-0.075	0.787	0.825	0.760	0.721	0.713
	[-0.40]	[1.91]	[2.46]	[2.52]	[2.48]	[2.06]
$\log(size^i)$		8.890	9.077	8.963	8.687	8.092
$\beta^i_{ASJ,t}$		0.158	0.343	0.416	0.494	0.681
$\beta^i_{VXO,t}$		-0.992	-0.448	-0.216	0.002	0.485
nFirms		177.551	178.208	178.220	178.208	177.551

Table V
Portfolios Grouped by $\beta^i_{ASJ,t}$ and $\beta^i_{VXO,t}$, Post-Decimalization: 2003-2013

This table reports the quintile portfolios grouped by the individual asset's sensitivities of volatility asymmetry risk $\beta^i_{ASJ,t}$, and total volatility risk $\beta^i_{VXO,t}$, estimated by the pre-formation regression according to equation (25). At the beginning of month t, all stocks are grouped into deciles based on the previous period's sensitivities, returns corresponding to the period from month t to $t+1$ (predictive) are then averaged to form the portfolio return. The Returns are reported in percentage, and averaged across time. Each column named from 1 to 5 corresponds to the deciles from Low to High on the sorted characteristics. The column named "5-1" corresponds to the Long-Short portfolio of buying the highest and selling the lowest decile portfolios. Panel A reports the portfolios sorted on $\beta^i_{ASJ,t}$. Panel B reports the double sort first in $\beta^i_{VXO,t}$, then $\beta^i_{ASJ,t}$, then pooled across $\beta^i_{VXO,t}$ quintiles. Panel C and D reports the portfolios sorted on $\beta^i_{VXO,t}$. The robust t-statistics are reported in square brackets below the mean return, and are adjusted for Newey and West (1987) standard error with 12 lags (corresponding to 1-year). The rows named $\log(size^i)$ reports the average logarithm of the firm size; The rows named $\beta^i_{ASJ,t}$ and $\beta^i_{VXO,t}$ are the average sensitivities of the firm within each portfolios; The rows named nFirms are the average number of firms in each portfolio. Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 20030101 to 20131231, covering 9:30am to 4:00pm, resulting in a total of 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database.

Decile	5-1	1	2	3	4	5
A: Single Sorted on $\beta^i_{ASJ,t}$, Monthly, Recent Sample: 200301-201312						
r_{t+1}(%) (value weight)	0.846	0.917	1.108	1.144	1.244	1.763
	[3.80]	[1.86]	[3.14]	[3.26]	[2.61]	[3.28]
r_{t+1}(%) (equal weight)	0.529	0.973	1.053	1.184	1.304	1.502
	[3.01]	[1.48]	[2.15]	[2.26]	[2.19]	[1.99]
$\log(size^i)$		12.050	12.829	12.994	13.002	12.460
$\beta^i_{ASJ,t}$		-2.016	-0.052	0.633	1.395	3.585
nFirms		1297.879	1298.818	1298.856	1298.818	1297.879
B: Double Sorted on $\beta^i_{ASJ,t}$, controlling for $\beta^i_{VXO,t}$, Monthly, Recent Sample: 200301-201312						
r_{t+1}(%) (value weight)	0.674	1.110	1.103	1.245	1.287	1.784
	[3.12]	[2.83]	[2.94]	[3.28]	[3.00]	[3.56]
r_{t+1}(%) (equal weight)	0.601	0.888	1.114	1.197	1.336	1.488
	[2.69]	[1.47]	[2.18]	[2.29]	[2.34]	[2.24]
$\log(size^i)$		11.923	12.734	12.945	13.024	12.724
$\beta^i_{VXO,t}$		-0.514	-0.406	-0.354	-0.309	-0.180
$\beta^i_{ASJ,t}$		-1.605	-0.046	0.651	1.393	3.156
nFirms		258.723	259.659	259.686	259.659	258.723
C: Single Sorted on $\beta^i_{VXO,t}$, Monthly, Recent Sample: 200301-201312						
r_{t+1}(%) (value weight)	-0.019	1.489	1.293	1.011	1.152	1.471
	[-0.07]	[2.87]	[2.98]	[2.51]	[2.73]	[2.77]
r_{t+1}(%) (equal weight)	-0.080	1.346	1.229	1.125	1.057	1.266
	[-0.44]	[1.78]	[2.11]	[2.14]	[2.13]	[1.91]
$\log(size^i)$		12.667	13.215	13.042	12.645	11.767
$\beta^i_{VXO,t}$		-1.551	-0.659	-0.330	-0.028	0.807
nFirms		1297.879	1298.818	1298.856	1298.818	1297.879
D: Double Sorted on $\beta^i_{VXO,t}$, controlling for $\beta^i_{ASJ,t}$, Monthly, Recent Sample: 200301-201312						
r_{t+1}(%) (value weight)	-0.173	1.538	1.221	1.157	1.134	1.365
	[-0.66]	[3.45]	[2.87]	[3.22]	[2.81]	[2.91]
r_{t+1}(%) (equal weight)	-0.245	1.353	1.303	1.158	1.096	1.109
	[-1.17]	[2.07]	[2.30]	[2.24]	[2.15]	[1.77]
$\log(size^i)$		12.874	13.172	13.011	12.587	11.704
$\beta^i_{ASJ,t}$		0.287	0.591	0.708	0.830	1.132
$\beta^i_{VXO,t}$		-1.386	-0.655	-0.338	-0.031	0.646
nFirms		258.723	259.659	259.686	259.659	258.723

Table VI
Firm-Level Fama-MacBeth Cross-Sectional Regression on β's

This table reports the results for firm-level Fama and MacBeth (1973) cross-sectional regression controlling for firm's risk exposures, under various specifications. At the end of every month t, we estimate Equation (28), controlling for firm characteristics and risk exposures β's: firm size, $\log(size_t^i)$, Book-to-Market $\log(BM_t^i)$, $\beta_{MKT,t}, \beta_{VXO,t}, \beta_{ARSJ,t}$, all estimated up to time t. After obtaining the coefficients for every t, we report the time-series average and the Newey and West (1987) robust t-statistics adjusted for 24-lags (corresponding to two years). Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19930101 to 20131231, resulting in a total of 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database. All realized high-frequency measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

(1) Intercept	(2) $\log(\text{Size}_t^i)$	(3) $\log(\text{BM}_t^i)$	(4) $iVol_t$	(5) $\beta_{MKT,t}$	(6) $\beta_{VXO,t}$	(7) $\beta_{RSJ,t}$	(8) R^2_{Adj}
1.309							-0.000
[3.90]							
3.419	-0.176	0.002				0.035	0.017
[3.70]	[-3.12]	[0.04]				[2.89]	
3.685	-0.183	-0.008	-0.018			0.029	0.030
[4.56]	[-3.76]	[-0.23]	[-1.48]			[2.48]	
3.683	-0.182	-0.009	-0.019	0.032		0.028	0.032
[4.55]	[-3.73]	[-0.25]	[-1.53]	[1.16]		[2.31]	
3.577	-0.167	-0.003	-0.016	0.004	0.086		0.031
[4.44]	[-3.49]	[-0.10]	[-1.34]	[0.12]	[1.79]		
3.783	-0.192	-0.020	-0.018	0.055	-0.064	0.042	0.039
[4.69]	[-3.90]	[-0.56]	[-1.64]	[1.63]	[-0.70]	[2.09]	
3.419	-0.176	0.002				0.035	0.017
[3.70]	[-3.12]	[0.04]				[2.89]	
1.195			-0.003			0.020	0.023
[4.19]			[-0.26]			[1.68]	
1.221				0.036		0.023	0.008
[3.79]				[1.11]		[1.81]	
1.243					0.025	0.033	0.016
[3.91]					[0.24]	[1.70]	
1.229						0.026	0.005
[3.77]						[2.18]	

Table VII
Portfolios Grouped by Relative Signed Jump Variations

This table reports the portfolios grouped by the Relative Signed Jump Variation, RSJ_t^i and its alternative measure, Relative Threshold Signed Jump Variation, $rTSJ_t^i$, both derived by normalizing the Signed Jump Variations by the same period Realized Variance. At the beginning of time t, all stocks are grouped into deciles based on the previous period's Relative Signed Jump Variations, returns corresponding to the period from time t to $t+1$ are then equal weighted to form the portfolio return. The Returns are reported in percentage, and averaged across time. Each column named from 1 to 10 corresponds to the deciles from Low to High on the sorted characteristics. The column named "10-1" corresponds to the Long-Short portfolio of buying the highest and selling the lowest decile portfolios. Panel A reports the portfolios sorted on RSJ_t^i re-grouped weekly. Panel B reports the regrouping in monthly frequency. Panel C and D reports the portfolios sorted on the alternative measure of Signed Jump Variations. The robust t-statistics are reported in square brackets below the mean return, and are adjusted for Newey and West (1987) standard error with 12 lags. The rows named $\log(size^i)$ reports the average logarithm of the firm size; The rows named RSJ_t^i and $rTSJ_t^i$ are the average characteristics of the firm within each portfolios; The rows named nFirms are the average number of firms in each portfolio. Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks and 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database, and the weekly returns are compounded from daily holding period return within that week. The Relative Signed Jump measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

Decile	10-1	1	2	3	4	5	6	7	8	9	10
						A: Weekly, Sorted on RSJ_t^i					
$r_{t+1}(\%)$	-0.427	0.506	0.460	0.422	0.350	0.291	0.270	0.229	0.201	0.161	0.079
	[-12.85]	[6.46]	[5.16]	[4.63]	[3.95]	[3.40]	[3.30]	[2.82]	[2.50]	[2.09]	[1.13]
$\log(size^i)$		11.630	12.339	12.638	12.805	12.811	12.754	12.901	12.884	12.641	11.865
RSJ_t^i		-0.353	-0.171	-0.105	-0.060	-0.025	0.005	0.038	0.081	0.147	0.329
nFirms		623.145	627.865	627.902	627.366	619.887	609.530	620.357	626.450	627.864	622.448
						B: Monthly, Sorted on RSJ_t^i					
$r_{t+1}(\%)$	-0.548	1.515	1.370	1.254	1.212	1.146	1.156	1.082	1.077	1.032	0.967
	[-3.52]	[4.70]	[3.75]	[3.54]	[3.46]	[3.19]	[3.45]	[3.23]	[3.46]	[3.27]	[3.21]
$\log(size^i)$		11.394	12.033	12.376	12.624	12.779	12.805	12.868	12.820	12.571	11.786
RSJ_t^i		-0.218	-0.105	-0.067	-0.041	-0.020	-0.001	0.018	0.043	0.081	0.193
nFirms		629.163	630.270	630.377	630.282	629.754	628.984	629.254	629.536	630.270	629.079
						C: Weekly, Sorted on $rTSJ_t^i$					
$r_{t+1}(\%)$	-0.391	0.494	0.425	0.381	0.331	0.281	0.292	0.263	0.235	0.180	0.102
	[-12.25]	[6.23]	[4.88]	[4.25]	[3.79]	[3.44]	[3.56]	[3.18]	[2.81]	[2.23]	[1.43]
$\log(size^i)$		11.687	12.311	12.663	12.917	12.884	12.754	13.016	12.904	12.591	11.910
RSJ_t^i		-0.326	-0.156	-0.093	-0.051	-0.020	0.005	0.032	0.072	0.133	0.300
nFirms		625.695	627.864	627.835	627.174	596.960	553.638	603.005	626.229	627.865	625.514
						D: Monthly, Sorted on $rTSJ_t^i$					
$r_{t+1}(\%)$	-0.519	1.469	1.346	1.334	1.169	1.205	1.136	1.117	1.065	1.009	0.951
	[-3.76]	[4.64]	[3.92]	[3.82]	[3.32]	[3.59]	[3.33]	[3.33]	[3.20]	[3.10]	[3.14]
$\log(size^i)$		11.487	12.029	12.405	12.682	12.812	12.701	12.849	12.809	12.496	11.856
RSJ_t^i		-0.199	-0.098	-0.061	-0.037	-0.017	-0.001	0.017	0.039	0.074	0.172
nFirms		629.306	630.270	630.381	630.119	626.548	621.016	623.044	629.873	630.270	629.306

Table VIII
Portfolios Grouped by Realized Moments and RSJ^i

This table reports the portfolios grouped by the Realized $1st$-$4th$ Moments (Past Return, Realized Volatility, Realized Skewness and Realized Kurtosis). For panel A, at the beginning of time t, all stocks are grouped into deciles based on the previous period's Relative Signed Jump Variations, returns corresponding to the period from time t to $t+1$ are then equal weighted to form the portfolio return. The Returns are reported in percentage, and averaged across time. Robust Newey and West (1987) t-statistics are reported in square brackets and are adjusted for 24 lags, corresponding to one year. Each column named from 1 to 10 corresponds to the deciles from Low to High on the sorted characteristics. The column named "10-1" corresponds to the Long-Short portfolio of buying the highest and selling the lowest decile portfolios. For panel B and C, At the beginning of time t, all stocks are first grouped into deciles based on the previous period's "controlled for" characteristics. Second, within each characteristics decile, stock are grouped into deciles based on the previous period's "sorted on" characteristics. Third, returns corresponding to the period from time t to $t+1$ are then equal weighted to form the each portfolio return on the 10×10 grid. Finally, we average across the "controlled for" dimension, and result in 10 portfolios of "sorted on" characteristics, while maintaining an even mixture of the "controlled for" characteristics. Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19930101 to 20131231, resulting in a total of 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database. All realized high-frequency measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

A: Single Sort on Realized Moments, Monthly

Sorted On	10-1	1	2	3	4	5	6	7	8	9	10
Past Ret.	-0.796	1.829	1.274	1.145	1.042	1.012	1.102	1.128	1.060	1.078	1.033
	[-2.40]	[3.79]	[3.35]	[3.57]	[3.61]	[3.58]	[3.92]	[3.97]	[3.60]	[3.27]	[2.11]
R. Vol.	0.885	0.730	0.892	0.956	1.089	1.131	1.271	1.247	1.413	1.410	1.615
	[1.48]	[3.64]	[3.66]	[3.69]	[3.86]	[3.81]	[3.89]	[3.40]	[3.34]	[2.73]	[2.54]
R. Skew.	-0.242	1.253	1.258	1.225	1.166	1.190	1.080	1.263	1.114	1.167	1.011
	[-2.17]	[3.99]	[3.84]	[3.58]	[3.38]	[3.54]	[3.17]	[3.63]	[3.30]	[3.62]	[3.48]
R. Kurt.	-0.043	1.184	1.048	1.121	1.126	1.273	1.184	1.311	1.247	1.169	1.141
	[-0.20]	[3.25]	[2.64]	[2.94]	[3.19]	[3.59]	[3.44]	[4.05]	[4.12]	[3.89]	[4.10]

B: Double Sort on Realized Moments Controlling for RSJ^i, Monthly

Sorted On	10-1	1	2	3	4	5	6	7	8	9	10
Past Ret.	-0.470	1.659	1.279	1.199	1.120	1.145	1.059	1.055	1.057	1.070	1.189
	[-1.60]	[3.68]	[3.49]	[3.66]	[3.69]	[4.07]	[3.80]	[3.63]	[3.39]	[3.23]	[2.45]
R. Vol.	0.732	0.762	0.947	0.976	1.126	1.179	1.212	1.317	1.307	1.520	1.494
	[1.25]	[3.64]	[3.88]	[3.74]	[4.05]	[3.84]	[3.64]	[3.62]	[3.07]	[3.02]	[2.37]
R. Skew.	-0.079	1.130	1.221	1.185	1.169	1.222	1.216	1.241	1.218	1.159	1.051
	[-0.82]	[3.61]	[3.69]	[3.55]	[3.42]	[3.60]	[3.48]	[3.55]	[3.55]	[3.63]	[3.52]
R. Kurt.	-0.082	1.208	1.106	1.107	1.189	1.205	1.270	1.222	1.210	1.162	1.126
	[-0.41]	[3.33]	[2.93]	[3.03]	[3.28]	[3.46]	[3.80]	[3.74]	[3.88]	[3.91]	[3.92]

C: Double Sort on RSJ^i Controlling for Realized Moments, Monthly

Controlling For	10-1	1	2	3	4	5	6	7	8	9	10
Past Ret	-0.302	1.327	1.302	1.291	1.165	1.214	1.125	1.108	1.139	1.119	1.025
	[-2.72]	[4.26]	[3.79]	[3.62]	[3.38]	[3.60]	[3.41]	[3.32]	[3.35]	[3.52]	[3.37]
R. Vol.	-0.430	1.455	1.337	1.268	1.210	1.131	1.154	1.105	1.076	1.005	1.025
	[-3.21]	[4.66]	[4.00]	[3.69]	[3.68]	[3.28]	[3.31]	[3.24]	[3.26]	[3.18]	[3.26]
R. Skew.	-0.419	1.392	1.433	1.297	1.223	1.146	1.168	1.098	1.071	1.026	0.973
	[-3.18]	[4.32]	[3.92]	[3.61]	[3.46]	[3.40]	[3.44]	[3.40]	[3.36]	[3.22]	[3.19]
R. Kurt.	-0.523	1.487	1.384	1.311	1.189	1.171	1.168	1.088	1.019	1.041	0.963
	[-2.96]	[4.17]	[3.83]	[3.83]	[3.42]	[3.42]	[3.60]	[3.38]	[3.28]	[3.33]	[3.10]

Table IX
Firm-Level Fama-MacBeth Cross-Sectional Regression

This table reports the results for firm-level Fama and MacBeth (1973) cross-sectional regression controlling for firm characteristics, under various specifications. At the end of every month t, we estimate Equation (28), controlling for firm characteristics: firm size, $\log(size_t^i)$, Book-to-Market $\log(BM_t^i)$, Relative Signed Jump Variation RSJ_t^i, Realized Volatility RV_t^i, Realized Skewness RSK_t^i, Realized Kurtosis RKT_t^i, past 1-month return STR_t^i, past 2-12 month return MOM_t^i, past 13-60 month return LTR_t^i, all observed up to time t. After obtaining the coefficients for every t, we report the time-series average and the Newey and West (1987) robust t-statistics adjusted for 12-lags (corresponding to one year). Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19930101 to 20131231, resulting in a total of 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database. All realized high-frequency measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

(1) Intercept	(2) $\log(\text{Size}_t^i)$	(3) $\log(\text{BM}_t^i)$	(4) RSJ_t^i	(5) RV_t^i	(6) RSK_t^i	(7) RKT_t^i	(8) STR_t^i	(9) MOM_t^i	(10) LTR_t^i	(11) R^2_{Adj}
1.240										0.000
[3.77]										
3.204	-0.151	0.034								0.012
[3.76]	[-2.67]	[0.61]								
3.056	-0.141	0.043	-1.813							0.013
[3.63]	[-2.54]	[0.79]	[-4.60]							
3.090	-0.133	0.070	-1.661	-0.001	-0.063	-0.010				0.032
[3.77]	[-2.91]	[1.58]	[-4.60]	[-0.18]	[-1.88]	[-1.18]				
2.906	-0.135	0.031	-0.787	0.000	0.054	-0.008	-0.024	0.004	-0.001	0.047
[3.76]	[-3.30]	[0.75]	[-2.66]	[0.05]	[1.78]	[-1.01]	[-5.42]	[1.14]	[-3.99]	
3.204	-0.151	0.034								0.012
[3.76]	[-2.67]	[0.61]								
1.305			-1.925							0.002
[4.30]			[-4.02]							
1.109				0.001	-0.165	0.004				0.025
[3.31]				[0.31]	[-4.29]	[0.50]				
1.100			-1.659	0.001	-0.081	0.004				0.026
[3.28]			[-4.35]	[0.22]	[-2.45]	[0.55]				
1.123							-0.022	0.002	-0.002	0.023
[3.17]							[-5.03]	[0.37]	[-3.59]	
1.111			-1.004				-0.020	0.002	-0.002	0.024
[3.14]			[-2.53]				[-4.45]	[0.40]	[-3.58]	

Table X
Portfolios Controlling for Other Firm-Level Characteristics

This table reports the portfolios grouped by the Relative Signed Jump Variation, RSJ_t^i and controlling for other firm-level characteristics, using 10×10 double sort. At the beginning of time t, all stocks are first grouped into deciles based on the previous period's firm-level characteristics. Second, within each characteristics decile, stock are grouped into deciles based on the previous period's Relative Signed Jump Variations. Third, returns corresponding to the period from time t to $t+1$ are then equal weighted to form the each portfolio return on the 10×10 grid. Finally, we average across the first sorted dimension, and result in 10 portfolios sorted on Relative Signed Jump Variations, while maintaining an even mixture of the controlling characteristics. The Returns are reported in percentage, and averaged across time. Each column named from 1 to 10 corresponds to the deciles from Low to High on the sorted characteristics. The column named "10-1" corresponds to the Long-Short portfolio of buying the highest and selling the lowest decile portfolios. Panel A and B reports the portfolios controlling for Realized Skewness and Realized Kurtosis as in Amaya et al. (2013) re-grouped weekly and monthly. Panel C reports the portfolios controlling for Short-Term-Reversal, as in Jegadeesh (1990). The robust t-statistics are reported in square brackets below the mean return, and are adjusted for Newey and West (1987) standard error with 12 lags. The rows named $\log(size^i)$ reports the average logarithm of the firm size; The row named RSJ_t^i is the average characteristics of the firm within each portfolios; The rows named nFirms are the average number of firms in each portfolio. Data covers all 19896 stocks available in TAQ (Trade and Quote) database, and all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks and 252 months. The return data are obtained from CRSP(Center for Research in Stock Prices) database, and the weekly returns are compounded from daily holding period return within that week. The Relative Signed Jump measures are constructed from the intra-day 5-minute return from TAQ covering 9:30am to 4:00pm.

Decile	10-1	1	2	3	4	5	6	7	8	9	10
					A1: Weekly, Controlling for Realized Skewness						
$r_{t+1}(\%)$	-0.292	0.420	0.436	0.392	0.350	0.322	0.290	0.238	0.218	0.189	0.128
	[-10.60]	[5.97]	[5.26]	[4.75]	[4.39]	[4.12]	[3.80]	[3.24]	[3.05]	[2.72]	[2.21]
$\log(size^i)$		11.826	12.493	12.658	12.631	12.748	12.743	12.711	12.769	12.667	11.994
$RSkew_t^i$		-0.104	-0.071	-0.057	-0.063	-0.047	-0.049	-0.043	-0.045	-0.031	0.004
RSJ_t^i		-0.305	-0.157	-0.102	-0.064	-0.029	0.005	0.040	0.079	0.135	0.287
nFirm		61.312	62.549	61.697	60.653	61.628	61.623	60.698	60.943	62.458	61.194
					A2: Monthly, Controlling for Realized Skewness						
$r_{t+1}(\%)$	-0.419	1.392	1.433	1.297	1.223	1.146	1.168	1.098	1.071	1.026	0.973
	[-3.32]	[4.49]	[3.80]	[3.44]	[3.42]	[3.36]	[3.56]	[3.56]	[3.60]	[3.58]	[3.91]
$\log(size^i)$		11.592	12.205	12.465	12.590	12.687	12.738	12.733	12.717	12.546	11.886
$RSkew_t^i$		-0.060	-0.053	-0.050	-0.048	-0.045	-0.047	-0.045	-0.044	-0.040	-0.034
RSJ_t^i		-0.199	-0.101	-0.066	-0.042	-0.022	-0.002	0.018	0.042	0.077	0.177
nFirm		61.925	62.992	62.964	62.885	62.615	62.601	62.827	62.870	62.987	61.915
					B1: Weekly, Controlling for Realized Kurtosis						
$r_{t+1}(\%)$	-0.500	0.580	0.462	0.377	0.333	0.290	0.251	0.250	0.201	0.153	0.081
	[-12.96]	[7.04]	[5.66]	[4.73]	[4.26]	[3.80]	[3.42]	[3.45]	[2.87]	[2.24]	[1.27]
$\log(size^i)$		12.311	12.421	12.487	12.576	12.594	12.486	12.658	12.686	12.669	12.574
$RKurt_t^i$		19.195	19.046	19.001	19.010	18.990	18.738	18.962	19.019	19.077	19.202
RSJ_t^i		-0.319	-0.177	-0.113	-0.065	-0.027	0.006	0.042	0.088	0.153	0.299
nFirm		61.339	62.564	62.683	62.424	60.094	58.233	61.037	62.397	62.556	61.277
					B2: Monthly, Controlling for Realized Kurtosis						
$r_{t+1}(\%)$	-0.523	1.487	1.384	1.311	1.189	1.171	1.168	1.088	1.019	1.041	0.963
	[-2.66]	[4.02]	[3.63]	[3.60]	[3.43]	[3.56]	[3.70]	[3.67]	[3.49]	[3.65]	[3.63]
$\log(size^i)$		11.987	12.191	12.305	12.425	12.512	12.561	12.602	12.627	12.637	12.450
$RKurt_t^i$		18.821	18.765	18.723	18.718	18.711	18.713	18.726	18.739	18.779	18.830
RSJ_t^i		-0.199	-0.108	-0.071	-0.044	-0.022	-0.001	0.021	0.047	0.083	0.176
nFirm		61.934	63.019	62.991	63.005	62.692	62.470	62.787	62.854	63.014	61.923
					C1: Weekly, Controlling for Short-Term Reversal						
$r_{t+1}(\%)$	-0.314	0.425	0.406	0.385	0.345	0.297	0.282	0.256	0.246	0.169	0.111
	[-13.98]	[6.62]	[5.40]	[4.90]	[4.37]	[3.82]	[3.68]	[3.35]	[3.26]	[2.34]	[1.83]
$\log(size^i)$		11.656	12.363	12.649	12.777	12.787	12.805	12.845	12.790	12.544	11.780
STR_t^i		0.959	1.009	1.021	1.028	1.052	1.100	1.147	1.182	1.215	1.194
RSJ_t^i		-0.336	-0.166	-0.102	-0.059	-0.026	0.005	0.037	0.079	0.142	0.312
nFirm		61.397	62.570	62.612	62.329	61.387	60.750	61.558	62.252	62.542	61.343
					C2: Monthly, Controlling for Short-Term Reversal						
$r_{t+1}(\%)$	-0.302	1.327	1.302	1.291	1.165	1.214	1.125	1.108	1.139	1.119	1.025
	[-3.18]	[4.69]	[3.92]	[3.75]	[3.44]	[3.50]	[3.37]	[3.39]	[3.53]	[3.67]	[3.83]
$\log(size^i)$		11.400	12.087	12.469	12.691	12.821	12.871	12.877	12.775	12.454	11.629
STR_t^i		0.845	0.953	0.971	1.039	1.106	1.175	1.237	1.339	1.416	1.412
RSJ_t^i		-0.196	-0.097	-0.062	-0.039	-0.020	-0.003	0.016	0.038	0.072	0.173
nFirm		61.958	62.967	63.019	62.961	62.699	62.642	62.871	62.930	62.956	61.948

Table XI
Fama-MacBeth Factor Prices, Monthly Horizon, Full and Rolling Beta

This table shows the Fama and MacBeth (1973) two step factor prices estimation results on the monthly horizon, using the $10\beta^i_{\Delta VXO} \times 10\beta^i_{ARSJ^m}$ portfolios in Table IV. Robust t-statistics are reported in square brackets, and with first-stage robust covariance matrix estimated according to the Newey and West (1987) estimator with 12 lags. For the full sample beta, t-statistics are accounted for errors-in-variables from the first stage regressions, following Shanken (1992). Before starting the two step estimation procedure, for each factor model specification, the factors are passed through a VAR(1) filter to obtain the orthogonalized innovations, following Campbell (1996). For the "Full Beta", the first-stage betas are estimated for the full sample, and for the "Rolling Beta", the first-stage betas are estimated on 5-year rolling window to account for potential changes in factor loadings, following Ferson and Harvey (1999). The zero-cost factor portfolios are added to the test assets, following Lewellen et al. (2010). Column (1) indicates the setup; Column (2) reports the estimated model intercepts; Columns (3),(4),(5) report the Fama and French (1993) 3-Factor, $MKT - r^f, SMB, HML$ prices, respectively; Columns (6),(7),(8) report the factor prices of momentum factors, i.e. medium-term MOM, long-term LTR and short-term STR factors, respectively; Columns (9), (10), (11), (12) reports the factor prices coefficient for the innovations in the weekly realized volatility, upside semi-variance, downside semi-variance and signed jump variation of SPY, respectively; Column (13) reports the adjusted R^2 in the second-stage. Data covers all trading days from 19930101 to 20131231. The daily factor portfolios $MKT - r^f, SMB, HML, MOM, LTR, STR$ and risk-free rate r_f are downloaded from Ken-French data library.

(1) Assets	(2) γ_0	(3) γ_{MKT}	(4) γ_{SMB}	(5) γ_{HML}	(6) γ_{MOM}	(7) γ_{LTR}	(8) γ_{STR}	(9) $\gamma_{\Delta RV^m}$	(10) $\gamma_{\Delta RV^{m,+}}$	(11) $\gamma_{\Delta RV^{m,-}}$	(12) $\gamma_{\Delta ARSJ^m}$	(13) R^2_{Adj}
Full Beta	0.166	0.737	0.346	0.211	0.080	0.240	0.328					0.356
$T = 252$	[0.68]	[1.94]	[1.19]	[0.73]	[0.18]	[0.75]	[0.79]					
nPf= 106	0.029	0.866	0.413	0.254	0.061	0.388	0.474	-0.445				0.371
	[0.13]	[2.42]	[1.44]	[0.88]	[0.14]	[1.24]	[1.20]	[-1.87]				
	0.112	0.766	0.285	0.313	0.114	0.327	0.356		-0.190	-0.325		0.407
	[0.53]	[2.16]	[1.00]	[1.07]	[0.27]	[1.03]	[0.89]		[-1.87]	[-2.38]		
	0.202	0.684	0.242	0.299	0.126	0.249	0.267				0.127	0.405
	[0.81]	[1.78]	[0.83]	[1.02]	[0.29]	[0.76]	[0.64]				[2.43]	
	0.112	0.766	0.285	0.313	0.114	0.327	0.356	-0.515			0.135	0.407
	[0.53]	[2.16]	[1.00]	[1.07]	[0.27]	[1.03]	[0.89]	[-2.20]			[2.56]	
Rolling Beta	0.085	0.817	0.351	-0.058	-0.324	0.012	0.451					0.358
$T = 252$	[0.42]	[2.26]	[1.63]	[-0.23]	[-1.36]	[0.07]	[2.06]					
nPf= 106	0.051	0.865	0.417	-0.100	-0.348	0.046	0.561	-0.301				0.345
	[0.25]	[2.39]	[1.90]	[-0.42]	[-1.44]	[0.31]	[2.58]	[-2.70]				
	0.043	0.883	0.422	-0.084	-0.285	0.052	0.535		-0.130	-0.180		0.346
	[0.21]	[2.50]	[1.97]	[-0.37]	[-1.17]	[0.34]	[2.50]		[-2.96]	[-2.77]		
	0.100	0.803	0.360	-0.070	-0.312	-0.025	0.453				0.042	0.335
	[0.50]	[2.25]	[1.68]	[-0.29]	[-1.31]	[-0.15]	[2.07]				[1.41]	
	0.043	0.883	0.422	-0.084	-0.285	0.052	0.535	-0.309			0.050	0.346
	[0.21]	[2.50]	[1.97]	[-0.37]	[-1.17]	[0.34]	[2.50]	[-2.90]			[1.73]	

Table XII
Fama-MacBeth Estimation on Alternative Test Assets, Weekly Horizon, Rolling Beta

This table shows the Fama and MacBeth (1973) two step factor prices on the weekly horizon. Robust t-statistics are reported in square brackets and accounted for errors-in-variables from the first stage regressions, following Shanken (1992), and with first-stage robust covariance matrix estimated according to the Newey and West (1987) estimator with 12 lags[14]. Before starting the two step estimation procedure, for each factor model specification, the factors are passed through a VAR(1) filter to obtain the orthogonalized innovations, following Campbell (1996). The first-stage is estimated on 5-year rolling window betas to account for potential changes in factor loadings, following Ferson and Harvey (1999). The zero-cost factor portfolios are added to the test assets, following Lewellen et al. (2010). Column (1) indicates the test assets chosen, i.e., 25 Size × BE/ME, 25 Size × Momentum, 25 Size × Long Term Reversal and 25 Size × Short Term Reversal portfolios, all in excess return; Column (2) reports the estimated model intercepts; Columns (3),(4),(5) report the Fama and French (1993) 3-Factor, $MKT - r^f, SMB, HML$ prices, respectively; Columns (6),(7),(8) report the factor prices of momentum factors, i.e. medium-term MOM, long-term LTR and short-term STR factors, respectively; Columns (9), (10), (11), (12) reports the factor prices coefficient for the innovations in the weekly realized volatility, upside semi-variance, downside semi-variance and signed jump variation of SPY, respectively; Column (13) reports the adjusted R^2 in the second-stage. Data covers all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks. The daily factor portfolios $MKT - r^f, SMB, HML, MOM, LTR, STR$ and risk-free rate r^f are downloaded from Ken-French data library and compounded to calendar weekly. The market realized variance (semi-variance, signed jump variation) are constructed from the intra-day 5-minute return of SPY from 9:30am to 4:00pm, obtained from NYSE TAQ (Trade and Quote) database, the weekly measures are the averaged daily measures during the corresponding week.

(1) Assets	(2) γ_0	(3) γ_{MKT}	(4) γ_{SMB}	(5) γ_{HML}	(6) γ_{MOM}	(7) γ_{LTR}	(8) γ_{STR}	(9) $\gamma_{\Delta RV^p}$	(10) $\gamma_{\Delta RV^{p,+}}$	(11) $\gamma_{\Delta RV^{p,-}}$	(12) $\gamma_{\Delta SJ^p}$	(13) R^2_{Adj}
25SZBM	0.050	0.066	0.025	0.055	0.077	0.006	0.226					0.598
T=1095	[4.15]	[0.72]	[0.51]	[1.06]	[0.89]	[0.14]	[2.81]					
nPf=31	0.044	0.073	0.020	0.062	0.071	0.016	0.237	-0.394				0.599
	[4.03]	[0.80]	[0.40]	[1.22]	[0.81]	[0.37]	[2.96]	[-2.05]				
	0.047	0.076	0.023	0.069	0.063	0.015	0.229		-0.111	-0.309		0.645
	[4.58]	[0.83]	[0.47]	[1.33]	[0.72]	[0.36]	[2.83]		[-1.32]	[-2.69]		
	0.049	0.071	0.028	0.054	0.081	0.008	0.229				0.193	0.648
	[4.64]	[0.78]	[0.58]	[1.05]	[0.95]	[0.18]	[2.87]				[2.71]	
	0.047	0.076	0.023	0.069	0.063	0.015	0.229	-0.420			0.198	0.645
	[4.58]	[0.83]	[0.47]	[1.33]	[0.72]	[0.36]	[2.83]	[-2.24]			[2.75]	
25SZMOM	0.041	0.096	0.054	0.025	0.093	0.043	0.243					0.770
T=1095	[2.73]	[1.05]	[1.06]	[0.42]	[1.04]	[0.97]	[3.09]					
nPf=31	0.034	0.104	0.050	0.038	0.088	0.057	0.243	-0.350				0.794
	[2.53]	[1.14]	[1.00]	[0.67]	[0.97]	[1.33]	[3.04]	[-1.98]				
	0.033	0.095	0.052	0.029	0.075	0.060	0.257		-0.045	-0.196		0.785
	[2.48]	[1.02]	[1.02]	[0.52]	[0.81]	[1.37]	[3.21]		[-0.58]	[-1.82]		
	0.035	0.099	0.060	0.020	0.091	0.052	0.244				0.142	0.773
	[2.46]	[1.08]	[1.18]	[0.36]	[1.00]	[1.18]	[3.10]				[2.06]	
	0.033	0.095	0.052	0.029	0.075	0.060	0.257	-0.240			0.151	0.785
	[2.48]	[1.02]	[1.02]	[0.52]	[0.81]	[1.37]	[3.21]	[-1.38]			[2.24]	
25SZLTR	0.034	0.095	0.063	0.050	0.058	0.056	0.235					0.817
T=1095	[2.33]	[1.02]	[1.24]	[0.96]	[0.66]	[1.29]	[2.91]					
nPf=31	0.030	0.105	0.057	0.053	0.060	0.059	0.245	-0.232				0.819
	[2.12]	[1.13]	[1.12]	[1.01]	[0.68]	[1.35]	[3.02]	[-1.39]				
	0.030	0.102	0.059	0.056	0.061	0.054	0.250		0.004	-0.220		0.823
	[2.12]	[1.08]	[1.16]	[1.07]	[0.69]	[1.22]	[3.08]		[0.06]	[-2.33]		
	0.023	0.103	0.067	0.066	0.076	0.062	0.249				0.229	0.822
	[1.61]	[1.11]	[1.32]	[1.24]	[0.85]	[1.41]	[3.10]				[3.60]	
	0.030	0.102	0.059	0.056	0.061	0.054	0.250	-0.216			0.225	0.823
	[2.12]	[1.08]	[1.16]	[1.07]	[0.69]	[1.22]	[3.08]	[-1.35]			[3.59]	
25SZSTR	0.031	0.092	0.040	0.003	0.017	0.102	0.288					0.713
T=1095	[1.84]	[0.98]	[0.78]	[0.04]	[0.20]	[2.38]	[3.56]					
nPf=31	0.020	0.107	0.048	0.009	0.045	0.112	0.285	-0.058				0.741
	[1.20]	[1.14]	[0.94]	[0.15]	[0.50]	[2.60]	[3.49]	[-0.39]				
	0.020	0.106	0.063	-0.005	0.031	0.105	0.307		0.163	-0.192		0.788
	[1.29]	[1.13]	[1.22]	[-0.09]	[0.35]	[2.40]	[3.69]		[2.44]	[-1.95]		
	0.021	0.101	0.053	-0.007	0.033	0.114	0.294				0.377	0.726
	[1.33]	[1.08]	[1.04]	[-0.12]	[0.37]	[2.63]	[3.63]				[5.40]	
	0.020	0.106	0.063	-0.005	0.031	0.105	0.307	-0.028			0.355	0.788
	[1.29]	[1.13]	[1.22]	[-0.09]	[0.35]	[2.40]	[3.69]	[-0.18]			[5.10]	

Table XIII
Fama-MacBeth Estimation on Alternative Test Assets, Weekly Horizon, Full and Rolling Beta

This table shows the Fama and MacBeth (1973) two step factor prices on the weekly horizon. Robust t-statistics are reported in square brackets and accounted for errors-in-variables from the first stage regressions, following Shanken (1992), and with first-stage robust covariance matrix estimated according to the Newey and West (1987) estimator with 12 lags[15]. Before starting the two step estimation procedure, for each factor model specification, the factors are passed through a VAR(1) filter to obtain the orthogonalized innovations, following Campbell (1996). For the "Full Beta", the first-stage betas are estimated for the full sample, and for the "Rolling Beta", the first-stage betas are estimated on 5-year rolling window to account for potential changes in factor loadings, following Ferson and Harvey (1999). The zero-cost factor portfolios are added to the test assets, following Lewellen et al. (2010). Column (1) indicates the test assets chosen, i.e., 25 Size × BE/ME, 25 Size × Momentum, all in excess return; Column (2) reports the estimated model intercepts; Columns (3),(4),(5) report the Fama and French (1993) 3-Factor, $MKT - r^f, SMB, HML$ prices, respectively; Columns (6),(7),(8) report the factor prices of momentum factors, i.e. medium-term MOM, long-term LTR and short-term STR factors, respectively; Columns (9), (10), (11), (12) reports the factor prices coefficient for the innovations in the weekly realized volatility, upside semi-variance, downside semi-variance and signed jump variation of SPY, respectively; Column (13) reports the adjusted R^2 in the second-stage. Data covers all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks. The daily factor portfolios $MKT - r^f, SMB, HML, MOM, LTR, STR$ and risk-free rate r^f are downloaded from Ken-French data library, and the weekly measures are aggregated from daily measures by summing up the daily log-returns during the corresponding week[16]. The market realized variance (semi-variance, signed jump variation) are constructed from the intra-day 5-minute return of SPY from 9:30am to 4:00pm, obtained from NYSE TAQ (Trade and Quote) database, the weekly measures are the averaged daily measures during the corresponding week.

(1) Assets	(2) γ_0	(3) γ_{MKT}	(4) γ_{SMB}	(5) γ_{HML}	(6) γ_{MOM}	(7) γ_{LTR}	(8) γ_{STR}	(9) $\gamma_{\Delta RV^p}$	(10) $\gamma_{\Delta RV^{p,+}}$	(11) $\gamma_{\Delta RV^{p,-}}$	(12) $\gamma_{\Delta SJ^p}$	(13) R^2_{Adj}
25SZBM												
Full Beta	0.028	0.128	0.013	0.088	0.117	0.031	0.368					0.587
T = 1095	[3.02]	[1.71]	[0.30]	[2.02]	[1.65]	[0.74]	[5.58]					
nPf= 31	0.024	0.133	0.013	0.089	0.120	0.035	0.372	0.108				0.574
	[3.06]	[1.78]	[0.32]	[2.06]	[1.69]	[0.87]	[5.65]	[0.48]				
	0.032	0.138	0.013	0.068	0.111	0.021	0.371		0.268	0.027		0.636
	[3.73]	[1.84]	[0.32]	[1.58]	[1.57]	[0.51]	[5.63]		[2.30]	[0.18]		
	0.036	0.123	0.011	0.076	0.109	0.019	0.363				0.251	0.608
	[4.09]	[1.64]	[0.28]	[1.76]	[1.54]	[0.46]	[5.50]				[2.87]	
	0.032	0.138	0.013	0.068	0.111	0.021	0.371	0.296			0.241	0.636
	[3.73]	[1.84]	[0.32]	[1.58]	[1.57]	[0.51]	[5.63]	[1.15]			[2.74]	
Rolling Beta	0.047	0.074	0.028	0.053	0.080	0.009	0.229					0.600
T = 1095	[3.99]	[0.81]	[0.57]	[1.03]	[0.93]	[0.21]	[2.85]					
nPf= 31	0.041	0.082	0.022	0.063	0.075	0.020	0.241	-0.393				0.599
	[3.69]	[0.90]	[0.45]	[1.22]	[0.87]	[0.46]	[3.01]	[-2.06]				
	0.043	0.086	0.025	0.070	0.068	0.019	0.233		-0.104	-0.301		0.646
	[4.26]	[0.93]	[0.51]	[1.35]	[0.77]	[0.44]	[2.87]		[-1.26]	[-2.67]		
	0.046	0.081	0.030	0.055	0.085	0.011	0.232				0.196	0.650
	[4.41]	[0.89]	[0.61]	[1.05]	[0.98]	[0.26]	[2.91]				[2.75]	
	0.043	0.086	0.025	0.070	0.068	0.019	0.233	-0.405			0.198	0.646
	[4.26]	[0.93]	[0.51]	[1.35]	[0.77]	[0.44]	[2.87]	[-2.20]			[2.76]	
25SZMOM												
Full Beta	-0.022	0.176	0.044	0.143	0.136	0.120	0.435					0.809
T = 1095	[-2.37]	[2.33]	[1.02]	[2.85]	[1.91]	[2.96]	[6.63]					
nPf= 31	-0.015	0.178	0.039	0.125	0.127	0.117	0.427	-0.388				0.806
	[-1.48]	[2.36]	[0.91]	[2.70]	[1.77]	[2.87]	[6.48]	[-1.41]				
	-0.026	0.193	0.050	0.126	0.140	0.128	0.440		0.037	-0.230		0.809
	[-2.22]	[2.55]	[1.16]	[2.71]	[1.95]	[3.05]	[6.64]		[0.30]	[-1.44]		
	-0.023	0.190	0.047	0.122	0.136	0.125	0.436				0.256	0.816
	[-2.48]	[2.52]	[1.10]	[2.65]	[1.90]	[3.08]	[6.65]				[2.14]	
	-0.026	0.193	0.050	0.126	0.140	0.128	0.440	-0.193			0.267	0.809
	[-2.22]	[2.55]	[1.16]	[2.71]	[1.95]	[3.05]	[6.64]	[-0.75]			[2.19]	
Rolling Beta	0.039	0.104	0.056	0.026	0.094	0.045	0.245					0.772
T = 1095	[2.55]	[1.13]	[1.10]	[0.45]	[1.04]	[1.02]	[3.11]					
nPf= 31	0.032	0.113	0.054	0.039	0.089	0.060	0.245	-0.351				0.796
	[2.33]	[1.23]	[1.06]	[0.69]	[0.98]	[1.39]	[3.07]	[-1.98]				
	0.031	0.108	0.055	0.031	0.076	0.062	0.259		-0.046	-0.197		0.785
	[2.27]	[1.16]	[1.09]	[0.55]	[0.83]	[1.41]	[3.22]		[-0.60]	[-1.81]		
	0.033	0.110	0.063	0.023	0.090	0.055	0.246				0.142	0.773
	[2.26]	[1.20]	[1.23]	[0.40]	[1.00]	[1.25]	[3.12]				[2.04]	
	0.031	0.108	0.055	0.031	0.076	0.062	0.259	-0.243			0.151	0.785
	[2.27]	[1.16]	[1.09]	[0.55]	[0.83]	[1.41]	[3.22]	[-1.38]			[2.22]	

Table XIV
Fama-MacBeth Estimation on Alternative Test Assets, Monthly Horizon, Full Beta

This table shows the Fama and MacBeth (1973) two step factor prices on the weekly horizon. Robust t-statistics are reported in square brackets and accounted for errors-in-variables from the first stage regressions, following Shanken (1992), and with first-stage robust covariance matrix estimated according to the Newey and West (1987) estimator with 12 lags[17]. Before starting the two step estimation procedure, for each factor model specification, the factors are passed through a VAR(1) filter to obtain the orthogonalized innovations, following Campbell (1996). For the "Full Beta", the first-stage betas are estimated for the full sample, and for the "Rolling Beta", the first-stage betas are estimated on 5-year rolling window to account for potential changes in factor loadings, following Ferson and Harvey (1999). The zero-cost factor portfolios are added to the test assets, following Lewellen et al. (2010). Column (1) indicates the test assets chosen, i.e., 25 Size × BE/ME, 25 Size × Momentum, all in excess return; Column (2) reports the estimated model intercepts; Columns (3),(4),(5) report the Fama and French (1993) 3-Factor, $MKT - r^f, SMB, HML$ prices, respectively; Columns (6),(7),(8) report the factor prices of momentum factors, i.e. medium-term MOM, long-term LTR and short-term STR factors, respectively; Columns (9), (10), (11), (12) reports the factor prices coefficient for the innovations in the weekly realized volatility, upside semi-variance, downside semi-variance and signed jump variation of SPY, respectively; Column (13) reports the adjusted R^2 in the second-stage. Data covers all trading days from 19930101 to 20131231. The weekly period ends on every Friday, resulting in a total of 1095 trading weeks. The daily factor portfolios $MKT - r^f, SMB, HML, MOM, LTR, STR$ and risk-free rate r^f are downloaded from Ken-French data library, and the weekly measures are aggregated from daily measures by summing up the daily log-returns during the corresponding week[18]. The market realized variance (semi-variance, signed jump variation) are constructed from the intra-day 5-minute return of SPY from 9:30am to 4:00pm, obtained from NYSE TAQ (Trade and Quote) database, the weekly measures are the averaged daily measures during the corresponding week.

(1) Assets	(2) γ_0	(3) γ_{MKT}	(4) γ_{SMB}	(5) γ_{HML}	(6) γ_{MOM}	(7) γ_{LTR}	(8) γ_{STR}	(9) $\gamma_{\Delta RV^p}$	(10) $\gamma_{\Delta RV^{p},+}$	(11) $\gamma_{\Delta RV^{p},-}$	(12) $\gamma_{\Delta SJ^p}$	(13)
25SZBM	-0.008	0.633	0.211	0.373	0.605	0.322	0.351					0.641
$T = 252$	[-0.21]	[2.25]	[0.98]	[1.79]	[1.84]	[1.64]	[1.42]					
nPf= 31	-0.010	0.625	0.211	0.364	0.611	0.334	0.355	-0.297				0.633
	[-0.25]	[2.22]	[0.98]	[1.76]	[1.86]	[1.71]	[1.44]	[-1.16]				
	-0.019	0.650	0.198	0.374	0.604	0.373	0.352		-0.012	-0.199		0.664
	[-0.49]	[2.32]	[0.92]	[1.81]	[1.84]	[1.93]	[1.42]		[-0.10]	[-1.32]		
	-0.028	0.648	0.198	0.388	0.629	0.378	0.370				0.174	0.669
	[-0.74]	[2.30]	[0.92]	[1.87]	[1.91]	[1.94]	[1.50]				[2.55]	
	-0.019	0.650	0.198	0.374	0.604	0.373	0.352	-0.210			0.187	0.664
	[-0.49]	[2.32]	[0.92]	[1.81]	[1.84]	[1.93]	[1.42]	[-0.81]			[2.61]	
25SZMOM	-0.122	0.760	0.295	0.555	0.603	0.545	0.452					0.825
$T = 252$	[-2.68]	[2.68]	[1.34]	[2.40]	[1.82]	[2.84]	[1.80]					
nPf= 31	-0.135	0.768	0.288	0.555	0.624	0.565	0.466	-0.079				0.832
	[-2.92]	[2.71]	[1.31]	[2.40]	[1.88]	[2.96]	[1.85]	[-0.28]				
	-0.123	0.792	0.290	0.543	0.610	0.557	0.449		-0.042	-0.171		0.837
	[-2.63]	[2.80]	[1.32]	[2.35]	[1.84]	[2.91]	[1.79]		[-0.35]	[-1.06]		
	-0.106	0.778	0.291	0.526	0.586	0.544	0.434				0.136	0.831
	[-2.30]	[2.74]	[1.32]	[2.28]	[1.77]	[2.83]	[1.72]				[2.03]	
	-0.123	0.792	0.290	0.543	0.610	0.557	0.449	-0.212			0.129	0.837
	[-2.63]	[2.80]	[1.32]	[2.35]	[1.84]	[2.91]	[1.79]	[-0.77]			[1.86]	

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