Good Volatility, Bad Volatility, and the Cross Section of Stock Returns

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Abstract

Based on intraday data for a large cross section of individual stocks and newly developed econometric procedures, we decompose the realized variation for each of the stocks into separate so-called realized up and down semi-variance measures, or "good" and "bad" volatilities, associated with positive and negative high-frequency price increments, respectively. Sorting the individual stocks into portfolios based on their normalized good minus bad volatilities results in economically large and highly statistically significant differences in the subsequent portfolio returns. These differences remain significant after controlling for other firm characteristics and explanatory variables previously associated with the cross section of expected stock returns.

JEL classification: C13, C14, G11, G12

Keywords: Cross-sectional return variation; return predictability; high-frequency-data; semi-variance; jump variation.

I. Introduction

Asset return volatility is naturally decomposed into "good" and "bad" volatility associated with positive and negative price increments. Based on high-frequency intraday data for almost 20,000 individual stocks spanning more than 20 years, along with new econometric procedures, we show that stocks with relatively high good-to-bad ex post realized weekly volatilities earn substantially lower ex ante weekly returns than stocks with low good-to-bad volatility ratios. Our results remain robust to the inclusion of a variety of controls and systematic risk factors previously associated with the cross-sectional variation in expected stock returns, and cannot be accounted for by other high-frequency-based realized variation measures recently analyzed in the literature.

The relation between equity return and volatility has been extensively studied in the literature. Even though a number of studies have argued that variance risk is priced at the individual firm level (Adrian and Rosenberg (2008), Da and Schaumburg (2011), and Bansal, Kiku, Shaliastovich, and Yaron (2014)), with changes in variances commanding a negative risk premium, these cross-sectional relationships are generally not very strong. The strong negative relation between idiosyncratic volatility and future stock returns first documented by Ang, Hodrick, Xing, and Zhang (2006b) has also subsequently been called into question by several more recent studies (for a recent discussion of the idiosyncratic volatility puzzle and the many related empirical studies, see, e.g., Stambaugh, Yu, and Yuan (2015) and Hou and Loh (2016)). Meanwhile, another strand of the literature has argued that the notion of a traditional linear return-volatility tradeoff relationship is too simplistic, and that more accurate cross-sectional return predictions may be obtained by separately considering the pricing of "upside" and "downside" volatilities (see, e.g., Ang, Chen, and Xing (2006a), Farago and Tédongap (2018)), or higher order conditional moments (see, e.g., Harvey and Siddique (2000), Dittmar (2002), and Conrad, Dittmar, and Ghysels (2013)).

Set against this background, we rely on recent advances in financial econometrics coupled with newly available high-frequency intraday data for accurately measuring "good" and "bad" volatility in a large cross section of individual stocks. In parallel to the standard realized variance measure defined by the summation of high-frequency intraday squared returns (see, e.g., Andersen, Bollerslev, Diebold, and Labys (2001)), the pertinent up and down realized semi-variance measures of Barndorff-Nielsen, Kinnebrock, and Shephard (2010) are simply defined by the summation of the squared positive and negative intraday price increments, respectively. Rather than separately considering the two semi-variance measures, we focus on their relative difference as a succinct scale-invariant measure for each of the individual stock's good versus bad volatility. We show that this simple summary measure strongly predicts the cross-sectional variation in the future returns.

In particular, on sorting the individual stocks into portfolios based on their weekly relative good minus bad volatility measures, we document a value-weighted weekly return differential between the stocks in the lowest quintile and the stocks in the highest quintile of 29.35 basis points (bps), or about 15% per year. The corresponding robust t-statistic of 5.83 also far exceeds the more stringent hurdle rates for judging statistical significance recently advocated by Harvey, Liu, and Zhu (2015). These highly statistical significant spreads remain intact in equal-weighted portfolios, double portfolio sorts controlling for other higher order realized variation measures, as well as in firm-level Fama–MacBeth (1973) type cross-sectional predictability regressions that simultaneously control for other higher order realized variations measures and a long list of other firm characteristics previously associated with the cross section of expected stock returns, including firm size, book-to-market ratio, momentum, short-term reversal, and idiosyncratic volatility.

Our results are closely related to the recent work by Amaya, Christoffersen, Jacobs, and Vasquez (ACJV) (2016), and their finding of significant spreads in the weekly returns on portfolios comprised of stocks sorted according to a high-frequency-based realized skewness measure. However, while we confirm the key finding of ACJV that the realized skewness significantly negatively predicts the cross-sectional variation in weekly returns, this effect is completely reversed after controlling for the relative good minus bad volatility, with the realized skewness significantly *positively* predicting the future weekly returns. By contrast, the association between the relative good minus bad volatility remains highly statistically significant after controlling for the realized skewness with a value-weighted weekly quintile spread of 36.45 bps, even higher than the spread for the single-sorted quintile portfolios.

The difference between the realized up and down semi-variance measures formally (for increasingly finer sampled intraday returns) converges to the variation due to positive minus negative price discontinuities, or the signed squared price jumps. Intuitively, since the variation associated with continuous variation, or Brownian price increments, is symmetric and (in the limit) therefore the same for the up and down semi-variance measures, their difference only formally manifest variation stemming from jumps. Meanwhile, instead of this "raw" jump measure, we rely on the relative signed jump (RSJ) variation, defined as the difference between the up and down semi-variance measures divided by the total return variation. The high-frequency-based realized skewness measure of ACJV similarly converges to a scaled version of the price jumps raised to the third power.[1] However, RSJ provides a much easier to estimate and interpret summary measure, directly motivated by the idea that stocks with different levels of good versus bad volatility, as manifest in the form of price jumps, might be priced differently in the cross section.

To better understand the determinants of the RSJ effect, we relate the performance of RSJ-sorted portfolios to other firm characteristics, including firm size, volatility and illiquidity. Larger firms, in particular, tend to have better information disclosure, while firms with more stable prices tend to have less asymmetric information. Consistent with investor overreaction, we document that both of these sets of firms are indeed associated with weaker RSJ performance. We also find that the RSJ effect is stronger among more illiquid stocks, consistent with the idea that higher transaction costs limit the forces of arbitrage (see, e.g., Shleifer and Vishny (1997)). Taken together this therefore suggests that the predictability associated with RSJ may be driven by investor overreaction and limits to arbitrage. Further along these lines, our decomposition of the profitability of a simple RSJ-based strategy following the approach of Lo and MacKinlay (1990) suggests that most of the profits arise from autocovariances in the returns and the stock's own RSJ, as opposed to covariation with other stocks' RSJ, consistent with an overreaction-based explanation.

A number of studies have previously suggested that jumps may be priced differently from continuous price moves, both at the aggregate market level (see, e.g., Eraker,

[1]As discussed in Feunou, Jahan-Parvar, and Tedongap (2016), the signed jump variation may alternatively be interpreted as a high-frequency measure of skewness.

Johannes, and Polson (2003), Bollerslev and Todorov (2011b)), and in the cross section (see, e.g., Yan (2011), Cremers, Halling, and Weinbaum (2015)). In contrast to these studies which rely on additional information from options prices to identify jumps, our empirical investigations rely exclusively on actual high-frequency prices for each of the individual stocks. The study by Jiang and Yao (2013) also utilizes actual high-frequency data together with a specific test for jumps to show that firms with more jumps have higher returns in the cross section. However, they do not differentiate between positive and negative jumps, or good and bad volatility.[2]

Our cross-sectional pricing results are also related to Breckenfelder and Tédongap (2012) and the time-series regression results reported therein, in which the good minus bad realized semi-variance measure for the aggregate market portfolio negatively predicts future market returns. The equilibrium asset pricing model in Breckenfelder and Tédongap (2012), based on a representative investor with recursive utility and generalized disappointment aversion, also provides a possible explanation for this differential pricing of good versus bad volatility at the aggregate market level. The closely related model developed in Farago and Tédongap (2018) similarly implies the existence of a systematic risk factor explicitly related to downside aggregate market volatility. By contrast, our return predictability results rely on the firm specific good minus bad volatility measures, or the relative signed jump variation for the individual stocks.

The paper is also related to the recent work of Feunou, Jahan-Parvar, and Tedongap (2013), Feunou and Okou (2018), Feunou, Lopez Aliouchkin, Tedongap, and Xu

[2]In a different vein, Bollerslev, Li, and Todorov (2016) have recently documented that stocks that jump more tightly together with the market tend to have higher returns on average.

(2017), and Feunou, Jahan-Parvar, and Okou (2018) on downside volatility. The last two studies, in particular, rely on similar ideas and techniques to the ones used here for decomposing both the actual realized volatility and the options implied volatility, and in turn the volatility risk premium defined as the difference between the expected future volatility and the options implied volatility, into up and downside components. Deepening existing empirical results (see, e.g., Bollerslev, Tauchen, and Zhou (2009), Dreschler and Yaron (2011)), it appears that most of the return predictability associated with the variance risk premium is attributable to the downside portion of the premium, again underscoring the differential pricing of good versus bad volatility.

The rest of the paper is organized as follows: Section II formally defines the semi-variances and other realized measures that underlie our empirical findings. Section III discusses the high-frequency data used in the construction of the realized measures, together with the additional control variables that we also rely on. Section IV summarizes the key distributional features of the high-frequency realized measures, including the relative signed jump variation in particular. Section V presents our main empirical findings related to the cross-sectional variation in returns and firm level good minus bad volatility based on simple single-sorted portfolios, single-sorted portfolios with controls, double-sorted portfolios, including RSJ and firm characteristic sorted portfolios, as well as firm level cross-sectional regressions. Section VI provides further evidence on the RSJ-based portfolio performance and where the returns are coming from. Section VII concludes. More specific details about the data and the variable construction, along with more in depth econometric discussions of some of the empirical findings, are deferred to an Appendix. Additional empirical results and robustness checks are provided in the Supplementary Material.

II. Realized Variation Measures: Theory

The theoretical framework formally justifying the realized variation measures, and the up and down realized semi-variance measures in particular that underly our empirical investigations, are based on the notion of fill-in asymptotics, or increasingly finer sampled returns over fixed time-intervals. This section provides a brief summary of the relevant ideas and the actual estimators that we rely on.

To set out the notation, let p_T denote the logarithmic price of an arbitrary asset. The price is assumed to follow the generic jump diffusion process,

$$p_T \;=\; \int_0^T \mu_\tau d\tau \;+\; \int_0^T \sigma_\tau dW_\tau \;+\; J_T, \tag{1}$$

where μ and σ denote the drift and diffusive volatility processes, respectively, W is a standard Brownian motion, and J is a pure jump process, and the unit time-interval corresponds to a trading day. We will assume that high-frequency intraday prices $p_t, p_{t+1/n}, \ldots, p_{t+1}$ are observed at $n+1$ equally spaced times over the trading day $[t, t+1]$. We will denote the natural logarithmic discrete-time return over the ith time-interval on day $t+1$ by $r_{t+i/n} = p_{t+i/n} - p_{t+(i-1)/n}$.

The daily realized variance (RV) is then simply defined by the summation of these within-day high-frequency squared returns,

$$\mathrm{RV}_t \;=\; \sum_{i=1}^{n} r^2_{t-1+i/n}. \tag{2}$$

By well-known arguments (see, e.g., Andersen et al. (2001), Andersen, Bollerslev, Diebold, and Labys (2003)), the realized variance converges (for $n \to \infty$) to the quadratic variation comprised of the separate components due to "continuous" and "jump" price increments,

$$\text{(3)} \qquad \mathrm{RV}_t \;\to\; \int_{t-1}^{t} \sigma_s^2 ds \;+ \sum_{t-1 \leq \tau \leq t} J_\tau^2,$$

thus affording increasingly more accurate ex post measures of the true latent total daily price variation for ever finer sampled intraday returns.[3]

The realized variance measure in equation (2) does not differentiate between "good" and "bad" volatility. Instead, the so-called realized up and down semi-variance measures, originally proposed by Barndorff-Nielsen et al. (2010), decompose the total realized variation into separate components associated with the positive and negative high-frequency returns,

$$\text{(4)} \qquad \mathrm{RV}_t^+ \;=\; \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n}>0\}}, \qquad \mathrm{RV}_t^- \;=\; \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n}<0\}}.$$

[3]In practice, data limitations and market microstructure complications invariably put an upper limit on the value of n. As discussed further below, following common practice in the realized volatility literature, we rely on a 5-minute sampling scheme, or $1/n = 78$.

The positive and negative realized semi-variance measures obviously add up to the total daily realized variation, $\mathrm{RV}_t = \mathrm{RV}_t^+ + \mathrm{RV}_t^-$. Moreover, it is possible to show that

$$\mathrm{RV}_t^+ \;\to\; \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 ds \;+ \sum_{t-1\leq\tau\leq t} J_\tau^2 \mathbf{1}_{(J_\tau>0)},$$
$$\mathrm{RV}_t^- \;\to\; \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 ds \;+ \sum_{t-1\leq\tau\leq t} J_\tau^2 \mathbf{1}_{(J_\tau<0)}.$$

so that the separately defined positive and negative semi-variance measures converge to one-half of the integrated variance plus the sum of squared positive and negative jumps, respectively.

These limiting results imply that the difference between the semi-variances removes the variation due to the continuous component and thus only reflects the variation stemming from jumps. We will refer to this good minus bad realized volatility measure as the signed jump (SJ) variation,

$$\mathrm{SJ}_t \;=\; \mathrm{RV}_t^+ - \mathrm{RV}_t^- \;\to \sum_{t-1\leq\tau\leq t} J_\tau^2 \mathbf{1}_{(J_\tau>0)} \;-\, J_\tau^2 \mathbf{1}_{(J_\tau<0)}. \tag{5}$$

The level of the volatility differs substantially across different stocks. As such, the signed jump variation for a particular stock may appear relatively high/low in a cross-sectional sense because the overall level of the volatility for that particular stock is relatively high/low. To help circumvent this, we normalize the signed jump variation by the total realized variation, defining the relative signed jump variation,

$$\mathrm{RSJ}_t \;=\; \frac{\mathrm{SJ}_t}{\mathrm{RV}_t}. \tag{6}$$

This normalization naturally removes the overall volatility level from the SJ measure, rendering RSJ a scale-invariant measure of the signed jump variation restricted to lie between −1 and 1.

In addition to these realized variation measures based on the separately defined up and down intraday return variation, we also calculate the daily realized skewness (RSK),

$$\text{RSK}_t = \frac{\sqrt{n}\sum_{i=1}^{n} r_{t-1+i/n}^{3}}{\text{RV}_t^{3/2}}, \tag{7}$$

and realized kurtosis (RKT),

$$\text{RKT}_t = \frac{n\sum_{i=1}^{n} r_{t-1+i/n}^{4}}{\text{RV}_t^{2}}, \tag{8}$$

measures analyzed by ACJV. In parallel to the RSJ measure defined above, the limiting values (for $n \to \infty$) of the RSK and RKT measures similarly manifest functions of the variation attributable to jumps. In contrast to RSJ, however, which has a clear interpretation as a measure of the relative signed jump variation, RSK and RKT converge to scaled versions of the intraday jumps raised to the third and fourth power, respectively, and are not directly interpretable as standard measures of skewness and kurtosis.[4]

[4]Whereas the population mean of RV is invariant to the sampling frequency of the returns underlying the estimation, the population means of RSK and RKT depend directly on the frequency of the data used in their estimation. The Supplementary Material also provides direct evidence that the RSJ estimates are more robust across sampling frequencies than the estimates for RSK.

Furthermore, compared to the realized variation measures, the use of higher order (than two) return moments in the calculation of the realized skewness and kurtosis measures render them more susceptible to "large" influential observations, or outliers, and thus generally more difficult to precisely estimate.

Our main cross-sectional asset pricing analyses are conducted at the weekly frequency. This directly mirrors ACJV. We construct the relevant weekly realized variation measures by summing the corresponding daily realized variation measures over the week. Specifically, if day τ is a Tuesday, we compute the (annualized) weekly realized volatility as,[5]

$$\text{RVOL}_\tau^{\text{Week}} = \left(\frac{252}{5} \sum_{i=0}^{4} \text{RV}_{\tau-i} \right)^{1/2}, \tag{9}$$

while for the RSJ_t, RSK_t or RKT_t measures, their weekly equivalents are defined as,

$$\text{RM}_\tau^{\text{Week}} = \frac{1}{5} \left(\sum_{i=0}^{4} \text{RM}_{\tau-i} \right), \tag{10}$$

where RM_t refers to the relevant daily measure. For notational convenience, we will drop the explicit Week superscript and the time τ subscript in the sequel and simply refer to each of the weekly measures by their respective abbreviations.

We turn next to a discussion of the data that we use in actually implementing these measures, as well as the additional control variables that we also rely on in our portfolio sorts and cross-sectional pricing regressions.

[5] We also report the results for other definitions of a week in the Supplementary Material.

III. Data

Our empirical investigation relies on high-frequency intraday data obtained from the Trade and Quote (TAQ) database. The TAQ database contains consolidated intraday transactions data for all securities listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), NASDAQ and SmallCap issues, as well as stocks traded on Arca (formerly Pacific Stock Exchange) and other regional exchanges, resulting in a total of 19,896 unique securities over the Jan. 4, 1993 to Dec. 31, 2013 sample period when matched according to the Center for Research in Securities Prices (CRSP) unique PERMNO numbers. Following the extant literature, we use all common stocks listed on the NYSE, NASDAQ, and AMEX exchanges, with share codes 10 or 11 and prices between $5 and $1,000. We rely on the consolidated trade files provided by TAQ to extract second-by-second prices, but only keep the observations for Monday to Friday from 9:30 am to 4:00 pm. All-in-all, this leaves us with 1,085 calendar weeks, or around 20 million firm-week observations. Further details concerning the high-frequency data and our cleaning procedures are provided in Appendix A.1.

We also rely on the CRSP database for extracting daily and monthly returns, number of shares outstanding, and daily and monthly trading volumes for each of the individual stocks. To help avoid survivorship bias, we further adjust the individual stock returns for delisting, using the delisting return provided by CRSP as the return after the last trading day. We also use the stock distribution information from CRSP for calculating the overnight returns.[6] We rely on Kenneth R. French's Web site: (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data-library.html) for obtaining daily and monthly returns on the Fama–French–Carhart 4-factor (FFC4) portfolios.

Lastly, we employ a number of additional explanatory variables and firm characteristics previously associated with the cross-sectional variation in returns. These include: the CAPM beta (BETA), size (ME) and book-to-market ratio (BM) (Fama and French (1993)), medium-term price momentum (MOM) (Jegadeesh and Titman (1993)), weekly reversal (REV) (Lehmann (1990) and Jegadeesh (1990)), idiosyncratic volatility (IVOL) (Ang et al. (2006b)), coskewness (CSK) (Harvey and Siddique (2000) and Ang et al. (2006a)), cokurtosis (CKT) (Ang et al. (2006a)), the maximum (MAX) and minimum (MIN) daily return (Bali, Cakici, and Whitelaw (2011)), and illiquidity (ILLIQ) (Amihud (2002)). The data for most of these variables are obtained from the CRSP and Compustat databases. Our construction of each of these variables follow standard procedures, as further detailed in Appendix A.2.

IV. Realized Variation Measures: Empirical Distributions

Our calculation of the realized volatility measures are based on high-frequency transactions prices. We resort to a "coarse" 5-minute sampling scheme, resulting in 390 (78 $\times$ 5) return observations for the calculation of each of the individual firms' weekly realized

[6]The high frequency TAQ database only contains the raw prices without consideration of the price differences before and after any distributions.

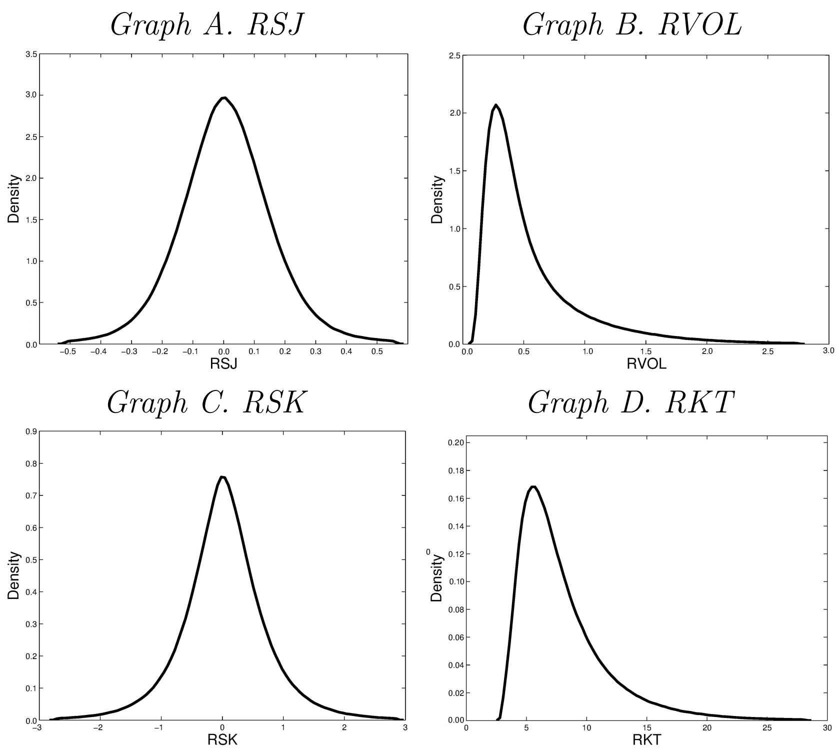
measures. Our choice of a 5-minute sampling scheme aims to balance the bias induced by market microstructure effects when sampling "too finely," and the theoretical continuous-time arguments underlying the consistency of the realized volatility measures that formally hinge on increasingly finer sample intraday returns. This particular choice also mirrors common practice in the literature (see, e.g., the survey in Hansen and Lunde (2006)).[7]

Figure 1 displays the kernel density estimates for the unconditional distributions of the resulting realized measures across all firms and weeks in the sample. Graph A, in particular, depicts the distribution of the new RSJ measure. The distribution is approximately symmetric around 0 with support almost exclusively between −0.5 and 0.5. This finding of approximately the same up and down semi-variance measures, or as implied by equation (5) close to identical positive and negative jump variation at the individual firm level, is in line with the previous evidence for the aggregate market portfolio and the close to symmetric high-frequency-based positive and negative jump tail distributions documented in Bollerslev and Todorov (2011a). Meanwhile, the unconditional distribution in Graph A still implies substantial variation in the RSJ measures across firms and time. From the summary statistics reported in Panel A of Table 1, the time-series mean of the

[7]This same choice was also adapted by ACJV in their construction of the high-frequency realized skewness and kurtosis measures, RSK and RKT. As discussed further in the Supplementary Material, we also experimented with the use of alternative subsampling estimators, high-frequency returns based on mid-quotes, and a sample of more liquid NYSE listed stocks only. Our empirical findings remain robust across all of these alternative estimators and more restricted sample.

cross-sectional standard deviations of RSJ equals 0.16. It follows readily from the definition in equation (6) that for a firm-week with RSJ 1 standard deviation above 0, the up semi-variance is approximately 38% larger than the down semi-variance, while for a firm-week with RSJ equal to 0.5, the up semi-variance is approximately three times as large as the down semi-variance.[8] As we document below, this nontrivial variation in the RSJ measures across firms and time is associated with strong cross-sectional return predictability.

Fig. 1: **Unconditional Distributions**
Graphs A–D show the kernel density estimates of the unconditional distributions of the RSJ, RVOL, RSK, and RKT realized measures, respectively, averaged across all firms and weeks in the sample.



[8]Formally, for a firm-week RSJ 1 standard deviation away from 0, $\sum_{i=0}^{4}\left(\{\mathrm{RV}^{+}_{t-i}-\mathrm{RV}^{-}_{t-i}\}/\{\mathrm{RV}^{+}_{t-i}+\mathrm{RV}^{-}_{t-i}\}\right)/5=0.16$. Thus, assuming that the ratios $\mathrm{RV}^{+}_{t-i}/\mathrm{RV}^{-}_{t-i}$ stay approximately constant within a week, this expression implies that RV^{+}_{t} is 38% higher than RV^{-}_{t}.

Table 1: **Descriptive Statistics**

Table 1 reports descriptive statistics for all of the main variables. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between $5 and $1,000 over the 1993–2013 sample period. RSJ, RVOL, RSK, and RKT denote the relative signed jump variation, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the standard CAPM beta. ME denotes the logarithm of the market capitalization of the firms. BM denotes the ratio of the book value of common equity to the market value of equity. MOM is the compound gross return from day $t-252$ through day $t-21$. REV is the lagged 1-week return. IVOL is a measure of idiosyncratic volatility. CSK and CKT are measures of coskewness and cokurtosis, respectively. MAX and MIN represent the maximum and minimum daily raw returns over the previous week. ILLIQ refers to the natural logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the previous week. Panel A reports the time-series average of the cross-sectional mean and standard deviation of each variable. Panel B reports the time-series average of the cross-sectional correlations of these variables. * and ** indicate significance at the 5% and 1% levels, respectively.

	RSJ	RVOL	RSK	RKT	BETA	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
Panel A. Cross-Sectional Summary Statistics															
Mean	0.01	0.61	0.04	7.75	1.11	6.99	0.55	0.26	0.01	0.02	-0.04	1.33	0.03	-0.03	-7.30
Std	0.16	0.41	0.77	3.96	0.54	1.58	0.63	0.65	0.07	0.01	0.29	0.80	0.04	0.04	4.08
Panel B. Cross-Sectional Correlations															
RSJ	1	−0.02**	0.93**	0.03**	−0.03**	0.00	0.01**	−0.01**	0.37**	−0.04**	0.00	0.01	0.24**	0.32**	0.00
RVOL		1	−0.02**	0.25**	0.15**	−0.60**	0.00	0.05**	0.04**	0.66**	0.00	−0.17**	0.33**	−0.24**	0.29**
RSK			1	0.04**	−0.02**	0.00	0.01**	−0.01**	0.27**	−0.03**	0.00	0.01*	0.19**	0.25**	0.00
RKT				1	−0.14**	−0.29**	0.04**	0.01**	0.00	0.11**	−0.01	−0.08**	0.00	0.04**	0.16**
BETA					1	0.27**	−0.15**	0.05**	−0.01*	0.30**	0.03**	0.21**	0.17**	−0.23**	0.04**
ME						1	−0.17**	0.02**	0.01*	−0.47**	0.01	0.22**	−0.15**	0.07**	−0.46**
BM							1	0.01	0.01**	−0.10**	−0.01	0.00	−0.02**	0.05**	0.05**
MOM								1	0.01*	0.11**	−0.02**	−0.01	0.04**	−0.05**	0.00
REV									1	0.03**	0.00	−0.02**	0.59**	0.51**	0.00
IVOL										1	−0.01	−0.31**	0.49**	−0.47**	0.17**
CSK											1	0.00	0.01*	0.02**	0.00
CKT												1	−0.07**	0.06**	−0.06**
MAX													1	0.05**	0.08**
MIN														1	−0.08**
ILLIQ															1

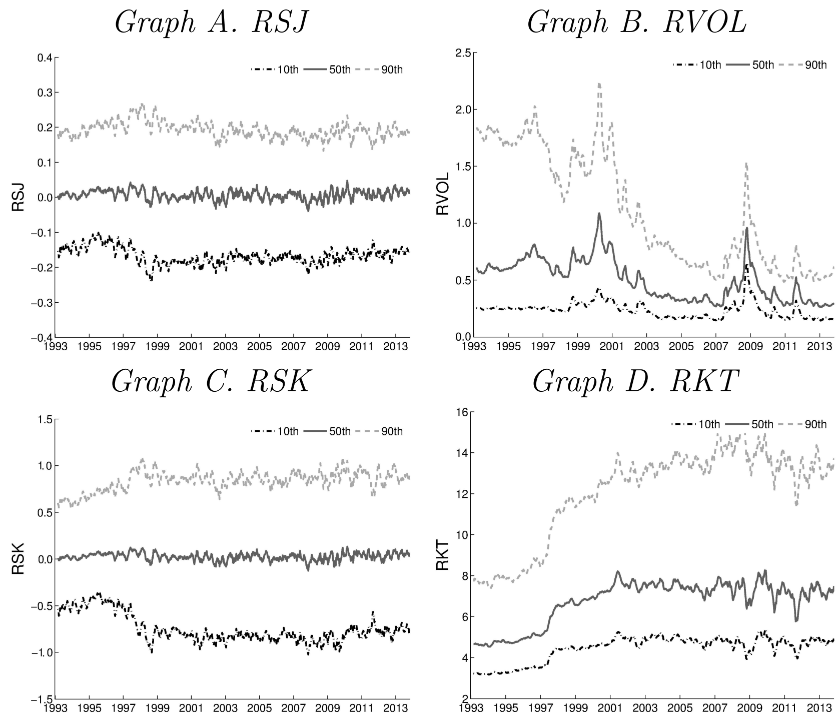
Mirroring the prior empirical evidence in ACJV, Graphs B–D in Figure 1 show the same across firm and time unconditional distributions for the RVOL, RSK and RKT realized measures. In parallel to the distribution of RSJ in Graph A, the distribution of RSK in Graph C is approximately symmetric. In comparison with RSJ, however, the distribution of RSK is substantially more heavy-tailed and peaked around 0.[9] The unconditional distributions of the realized volatility and kurtosis in Graphs B and D, respectively, are both heavily skewed to the right.

[9]The unconditional kurtosis of the RSK distribution equals 11.46, compared to 5.65 for RSJ.

To help illuminate the temporal variation in each of the realized measures implicit in these unconditional distributions, Figure 2 plots the 10-week moving averages of the 10th, 50th, and 90th percentile for the RSJ, RVOL, RSK, and RKT measures. The plot in Graph A reveals a remarkably stable dispersion in the distributions of the RSJ measures over time. The percentiles for RSK shown in Graph C also appear quite steady through time, albeit not as stable as those for RSJ. By contrast, the percentiles of the realized volatilities RVOL shown in Graph B are clearly time-varying, with marked peaks around the time of the burst of the dot-com bubble and the financial crisis of 2007–2008. Consistent with the recent findings in Herskovic et al. (2016) and the existence of a common factor structure in idiosyncratic, or firm-specific, volatilities, there is also a distinct commonality in the temporal variation in the RVOL percentiles. The apparent increase in the cross-sectional dispersion in the RKT measures observed in the final Graph D is inline with the evidence reported in ACJV.

Fig. 2: **Percentiles**

Graphs A–D display the 10-week moving average time-series percentiles of the RSJ, RVOL, RSK, and RKT realized measures, respectively, averaged across all firms in the sample.



Panel A in Table 1 provides the time-series averages of cross-sectional means and standard deviations for each of the four realized measures, as well as the other control variables that we also rely on in our analysis. Panel B of that same table reports the corresponding weekly cross-sectional correlations. RSJ and RSK are the two most highly correlated variables, with a highly significant correlation coefficient of 0.93. The new RSJ measure also correlates significantly with REV, MAX, and MIN with correlation coefficients of 0.37, 0.24, and 0.32, respectively, compared with the slightly lower correlations of 0.27, 0.19, and 0.25, respectively, for RSK.[10] This high pairwise correlation and similar

[10]The time-series plots of the four realized measures sorted by REV (Figure A.1), RSJ (Figure A.2) and RSK (Figure A.3) given in the Supplementary Material further illustrate the cross-sectional dependencies inherent in these correlations.

correlations with the other control variables are not necessarily surprising, as RSJ and RSK both reflect notions of asymmetry in the intraday return distributions. At the same time, however, our empirical results discussed below suggest that the return predictability afforded by RSJ is both stronger and more robust than the return predictability of RSK.

To further clarify the relation between the realized measures and the different control variables, we also employ a series of simple portfolio sorts. At the end of each Tuesday, we sort the stocks by their past weekly realized variation measures and form 5 equal-weighted portfolios. We then calculate the time-series averages of the various firm characteristics for the stocks within each of these quintile portfolios. The results based on these RSJ, RVOL, RSK, and RKT sorts are reported in Panels A–D of Table 2, respectively. Consistent with the correlations discussed above, the portfolio sorts reveal that high RSJ firms tend to be firms with high RSK, REV, MAX and low MIN.[11] Further, while firms with high RVOL and high RKT tend to be small and less liquid firms, there is no obvious relation between RSK and firm size and illiquidity. Instead, in parallel to the results for the RSJ sorts, firms with high RSK tend to have higher REV and MAX returns and lower MIN returns.

[11]The Supplementary Material provides additional cross-sectional regression-based evidence for a negative relationship between RSJ and firm leverage and credit ratings. None of these relations, are very strong, however.

Table 2: **Portfolio Characteristics Sorted by Realized Measures**

Table 2 displays time-series averages of equal-weighted characteristics of stocks sorted by the four realized measures. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between \$5 and \$1,000 over the 1993–2013 sample period. RSJ, RVOL, RSK, and RKT denote the relative signed jump variation, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the standard CAPM beta. ME denotes the logarithm of the market capitalization of the firms. BM denotes the ratio of the book value of common equity to the market value of equity. MOM is the compound gross return from day $t-252$ through day $t-21$. REV is the lagged 1-week return. IVOL is a measure of idiosyncratic volatility. CSK and CKT are measures of coskewness and cokurtosis, respectively. MAX and MIN represent the maximum and minimum daily raw returns over the previous week. ILLIQ refers to the natural logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the previous week. Panel A displays the results sorted by RSJ, Panel B by RVOL, Panel C by RSK, and Panel D by RKT.

Quintile	RSJ	RVOL	RSK	RKT	BETA	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
Panel A. Sorted by RSJ															
1 (Low)	-0.200	0.654	-0.888	8.990	1.094	6.757	0.553	0.270	-0.036	0.023	-0.038	1.292	0.019	-0.041	-7.024
2	-0.061	0.599	-0.247	6.886	1.158	7.115	0.536	0.256	-0.011	0.021	-0.036	1.350	0.030	-0.033	-7.447
3	0.007	0.588	0.026	6.676	1.150	7.174	0.542	0.250	0.007	0.021	-0.035	1.361	0.035	-0.028	-7.502
4	0.077	0.582	0.307	6.981	1.131	7.141	0.546	0.253	0.025	0.021	-0.036	1.353	0.039	-0.023	-7.475
5 (High)	0.227	0.620	0.985	9.207	1.037	6.759	0.574	0.250	0.046	0.021	-0.038	1.296	0.047	-0.009	-7.024
Panel B. Sorted by RVOL															
1 (Low)	0.014	0.231	0.050	6.695	0.807	8.469	0.550	0.171	0.004	0.011	-0.037	1.457	0.018	-0.014	-8.860
2	0.013	0.351	0.046	7.052	1.013	7.710	0.558	0.190	0.004	0.015	-0.034	1.451	0.025	-0.020	-8.027
3	0.010	0.503	0.040	7.518	1.197	6.975	0.544	0.270	0.005	0.019	-0.036	1.375	0.032	-0.026	-7.347
4	0.009	0.721	0.034	8.039	1.321	6.295	0.529	0.331	0.007	0.025	-0.035	1.277	0.041	-0.032	-6.603
5 (High)	0.004	1.236	0.012	9.444	1.230	5.495	0.571	0.314	0.011	0.036	-0.040	1.093	0.056	-0.040	-5.642
Panel C. Sorted by RSK															
1 (Low)	-0.189	0.665	-0.942	9.600	1.083	6.710	0.552	0.274	-0.026	0.023	-0.038	1.291	0.023	-0.038	-6.989
2	-0.059	0.593	-0.255	6.516	1.155	7.137	0.538	0.256	-0.008	0.021	-0.036	1.351	0.031	-0.032	-7.454
3	0.007	0.578	0.026	6.160	1.152	7.225	0.545	0.245	0.007	0.021	-0.035	1.361	0.034	-0.028	-7.559
4	0.075	0.576	0.313	6.607	1.136	7.166	0.544	0.253	0.021	0.021	-0.036	1.351	0.038	-0.024	-7.482
5 (High)	0.215	0.631	1.041	9.859	1.044	6.708	0.573	0.250	0.037	0.021	-0.038	1.299	0.044	-0.012	-6.990
Panel D. Sorted by RKT															
1 (Low)	0.005	0.493	0.015	4.371	1.177	7.869	0.533	0.211	0.005	0.018	-0.031	1.428	0.031	-0.026	-8.306
2	0.007	0.570	0.021	5.587	1.164	7.237	0.534	0.257	0.006	0.020	-0.036	1.370	0.034	-0.028	-7.616
3	0.008	0.609	0.027	6.760	1.136	6.902	0.541	0.268	0.007	0.022	-0.038	1.324	0.036	-0.028	-7.235
4	0.011	0.641	0.039	8.439	1.097	6.645	0.555	0.274	0.007	0.023	-0.039	1.286	0.036	-0.028	-6.873
5 (High)	0.019	0.728	0.081	13.590	0.994	6.291	0.589	0.267	0.006	0.023	-0.039	1.244	0.034	-0.024	-6.448

We turn next to a discussion of how similarly constructed portfolio sorts manifest in future return differentials.

V. Good Minus Bad Variation and Future Stock Returns

We begin our empirical investigations related to return predictability by documenting highly statistically significant negative spreads in the returns on quintile portfolios comprised of stocks sorted according to their individual relative signed jump variation measure RSJ, and their realized skewness measure RSK. We then show that the spreads based on RSJ remain highly significant in double portfolio sorts designed to control for other higher order realized variation measures and control variables. By contrast, the double portfolio sorts based on RSK that control for RSJ results in the completely opposite cross-sectional relation, with high/low RSK firms associated with higher/lower future returns. We further corroborate these findings in firm level cross-sectional return predictability regressions that simultaneously control for multiple higher order realized measures and other firm characteristics.

A. Single-Sorted Portfolios

Following the identical approach employed in the previous section, at the end of each Tuesday, we sort the stocks into quintile portfolios based on their realized variation measures. We then compute value- and equal-weighted returns over the subsequent week for each of these different quintile portfolios. We also report the results for a self-financing long-short portfolio that buys stocks in the top quintile and sells stocks in the bottom quintile.

Table 3: **Predictive Single-Sorted Portfolios**

Table 3 reports the average returns for the predictive single-sorted portfolios. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between $5 and $1,000 over the 1993–2013 sample period. At the end of each week, stocks are sorted into quintiles according to realized measures computed from previous week high-frequency returns. Each portfolio is held for 1 week. The column labeled "Return" reports the average 1-week ahead excess returns of each portfolio. The column labeled "FFC4" reports the corresponding Fama–French–Carhart 4-factor alpha for each portfolio. The row labeled "High−Low" reports the difference in returns between portfolio 5 and portfolio 1, with Newey–West (1987) robust t-statistics in parentheses. RSJ, RVOL, RSK, and RKT denote the relative signed jump variation, realized volatility, realized skewness, and realized kurtosis, respectively. In each panel, the first 2 columns report the value-weighted sorting results and the last 2 columns report the equal-weighted sorting results. Panel A displays the results sorted by RSJ, Panel B by RVOL, Panel C by RSK, and Panel D by RKT.

Panel A. Sorted by RSJ

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	32.75	16.56	54.72	35.36
2	23.74	7.72	37.63	18.32
3	13.76	-1.80	29.20	10.00
4	7.74	-7.67	20.93	1.93
5 (High)	3.40	-12.24	16.18	-2.53
High−Low	-29.35	-28.80	-38.54	-37.89
	(-5.83)	(-5.77)	(-9.66)	(-9.95)

Panel B. Sorted by RVOL

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	15.99	2.07	19.60	4.79
2	17.14	-0.77	24.34	5.39
3	16.19	-3.42	26.59	6.20
4	19.36	-0.63	33.06	12.04
5 (High)	33.18	12.03	55.04	34.65
High−Low	17.19	9.96	35.45	29.86
	(1.29)	(1.18)	(3.57)	(5.46)

Panel C. Sorted by RSK

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	25.80	8.92	50.03	30.79
2	23.81	8.10	37.41	18.31
3	14.58	-0.57	28.36	9.08
4	9.53	-6.14	23.92	4.86
5 (High)	7.66	-8.19	18.94	0.05
High−Low	-18.14	-17.11	-31.09	-30.75
	(-4.35)	(-4.11)	(-9.79)	(-10.08)

Panel D. Sorted by RKT

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	15.41	0.55	26.96	8.94
2	19.10	2.57	31.60	12.04
3	18.18	1.20	33.23	13.00
4	18.40	1.81	32.56	13.01
5 (High)	14.53	-2.22	34.28	16.07
High−Low	-0.88	-2.77	7.32	7.13
	(-0.24)	(-0.85)	(2.29)	(2.60)

Panel A of Table 3 displays the weekly portfolio returns (in basis points) from sorting on RSJ. The column labeled "Return" for the value-weighted portfolios reveals a clear negative relation between the relative signed jump variation and the average future realized returns. The average weekly return decreases monotonically from 32.75 bps for Quintile 1 (Low) to 3.40 for Quintile 5 (High), yielding a High−Low spread of -29.35 bps, with a robust t-statistic of -5.83. The equal-weighted portfolio returns show the same decreasing pattern between RSJ and the returns over the subsequent week, with a High−Low spread of −38.54 bps per week.

To investigate whether these return differences result from exposure to systematic risks, we rely on the popular Fama–French–Cahart 4-factor model (Fama and French (1993), Carhart (1997)). In particular, we regress the excess returns for each of the quintile portfolios and the High−Low spread against the 4 factors for calculating the FFC4 alphas, defined as the regression intercepts. The column labeled "FFC4" shows a similarly strong negative relation between RSJ and the abnormal future returns measured in terms of these FFC4 alphas. The FFC4 alpha of the self-financing value-weighted RSJ strategy, in particular, equals −28.80 bps per week and remains highly significant with a t-statistic of −5.77, while for the equal-weighted portfolios the risk-adjusted FFC4 alpha for the High−Low spread equals −37.89 bps, with a t-statistics of −9.95.

The results for the RVOL, RSK and RKT single-sorted portfolios reported in Panels B–D in Table 3 confirm the findings in ACJV related to the predictability of these same realized measures. Panel C in particular, shows that there is a strong negative relation between the realized skewness and next week's stock returns. A strategy that buys stocks in the lowest realized skewness quintile and sell stocks in the highest realized skewness quintile generates an average abnormal return of −17.11 bps per week, with a robust t-statistics of −4.11 for the value-weighted portfolios, and −30.75 bps with a t-statistics of −10.08 for the equal-weighted portfolios.[12] On the other hand, the t-statistics associated

[12]The stronger RSJ and RSK effects observed for equal-weighted portfolios naturally raise the question of whether the two measures pick up a different feature for less-liquid small-cap stocks compared to more-liquid large-cap stocks. Still, recall that our current sample already is restricted

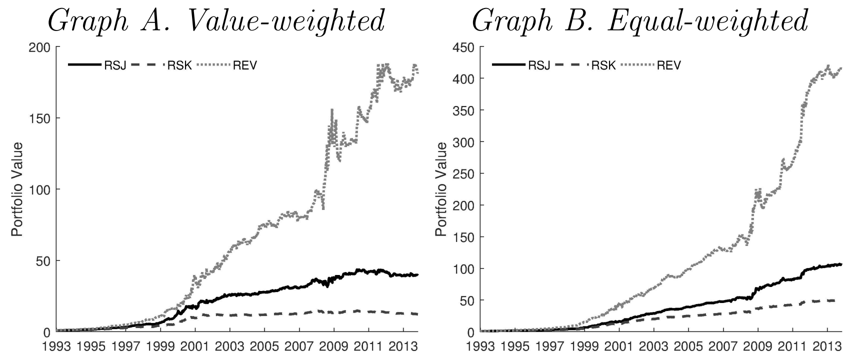
with the High−Low spreads based on RVOL and RSK in Panels B and D, respectively, are much smaller and statistically insignificant for the value-weighted portfolios. Thus, consistent with the vast existing empirical literature and the lack of a simple risk-return tradeoff relationship, there is at best scant evidence for the realized volatility and kurtosis measures being able to predict the future returns.

To help more clearly illuminate how the long-short portfolios based on the different realized variation measures perform over time, Graphs A and B in Figure 3 depict the cumulative profits for the resulting value-weighted and equal-weighted strategies based on an initial investment of $W_0 = \$1$. Specifically, let W_τ denote the cumulative profit at the end of week τ. The cumulative profits depicted in the figure are then calculated as $W_\tau = W_{\tau-1} \times (1 + r_{\mathrm{LONG},\tau} - r_{\mathrm{SHORT},\tau} + r_{f,\tau})$, where $r_{\mathrm{LONG},\tau}$ and $r_{\mathrm{SHORT},\tau}$ denote the weekly returns on the long-leg and the short-leg of the portfolio, respectively, and $r_{f,\tau}$ denotes the weekly risk-free rate.

to stocks listed on the NYSE, AMEX and NASDAQ exchanges, with share codes 10 or 11 and prices between \$5 and \$1,000. Nonetheless, in an effort to help further alleviate this concern, we repeated the single-sorting analyses using only the sample of the Standard & Poor's (S&P) 500 stocks. RSJ and RSK remain strong predictors for next-week returns within this more limited sample of stocks. In particular, when sorting by RSJ, the FFC4-adjusted High−Low spread equals −26.23 bps, with a t-statistic of −5.22, for the value-weighted portfolios, and −19.16 bps, with a t-statistic of −4.77, for the equal-weighted portfolios. We thank the referee for highlighting this issue.

Fig. 3: **Cumulative Portfolio Gains**

Graph A of Figure 3 shows the cumulative gains for a value-weighted long-short portfolio based on RSJ, RSK, or REV. Graph B shows the cumulative gains for an equal-weighted long-short portfolio. All of the portfolios are re-balanced and accumulated on a weekly basis, as described in the main text.



As Figure 3 shows, the RSJ-based strategy outperforms the RSK strategy by quite a wide margin.[13] Moreover, even though the value-weighted RSK-based strategy does result in statistically significant excess return when evaluated over the full sample, most of the superior performance occurs right around the collapse of the dot-com bubble, with almost "flat" returns post 2001. By contrast, the RSJ-based long-short strategy delivers superior returns throughout the sample, both for the value-weighted and equal-weighted portfolios. As a benchmark, the figure also reports the cumulative profits based on REV. The REV-based strategies obviously result in the largest overall cumulative profits.[14] Meanwhile, the correlation between the RSJ asymmetry measure and the REV return

[13]The (unreported) cumulative profits based on RKT and RVOL are both close to 0.

[14]Following the approach of Tulchinsky (2015), we also calculated the portfolio turnovers for the RSJ, RSK, and REV-based strategies to be 63.22%, 64.12% and 71.76%, respectively. Thus, the turnover is about the same for RSJ and RSK, and slightly higher for REV. Correspondingly, explicitly accounting for transaction costs, using the effective spread as a proxy (see, e.g., Hasbrouck (2009)), results in the highest net returns for the RSJ-based long-short strategy.

measure is only 0.37, and as such the two strategies effectively profits from different effects. The next section further delineates these separate effects.

B. Single-Sorted Portfolios with Controls

The sample correlations and the portfolio sorts reported in Tables 1 and 2, respectively, revealed a strong contemporaneous relation between the two RSJ and RSK realized measures, and somewhat weaker, albeit statistically significant, correlation with the weekly return reversal REV. To help clarify the unique informational content in each of the realized measures, we further sort the stocks by the residuals obtained from controlling for the past week returns. Specifically, at the end of each Tuesday, we run a cross-sectional regression of RSJ against REV, or RSK against REV, and sort the stocks based on the resulting regressions residuals.[15]

The results in Panel A of Table 4 shows that these RSJ residual-based sorts still negatively predict future returns. The weekly FFC4 alpha of the High−Low spreads equals −17.67 bps, with a t-statistic of −4.00, for the value-weighted portfolios, and −15.27 bps, with a t-statistic of −5.35, for the equal-weighted portfolios. These FFC4 alphas are smaller than those produced by the simple RSJ sorts in Panel A, indicating that part of the predictability of RSJ is indeed attributable to the short-term reversal effect. Nonetheless, the results remain economically and statistically significant, implying a

[15]This approach is useful in delineating the unique predictability in RSJ and RSK over and above that of REV, as the regression residuals are orthogonal to the regressor by construction.

substantial amount of additional information in the new RSJ measure beyond that of the weekly return reversal REV.

Table 4: **Predictive Single-Sorted Portfolios with Controls**

Table 4 reports the average returns for predictive single-sorted portfolios with controls. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between \$5 and \$1,000 over the 1993–2013 sample period. At the end of each week, stocks are sorted into quintiles according to realized measures with controls computed from previous week high-frequency returns. Each portfolio is held for 1 week. The column labeled "Return" reports the average 1-week ahead excess returns of each portfolio. The column labeled "FFC4" reports the corresponding Fama–French–Carhart 4-factor alpha for each portfolio. The row labeled "High−Low" reports the difference in returns between portfolio 5 and portfolio 1, with Newey–West robust t-statistics in parentheses. RSJ, RSK, and REV denote the relative signed jump variation, realized skewness, and lagged 1-week return, respectively. In each panel, the first 2 columns report the value-weighted sorting results and the last 2 columns report the equal-weighted sorting results. Panel A displays the results sorted by by RSJ residual controlling for REV, Panel B by RSK residual controlling for REV, Panel C by RSJ residual controlling for RSK, and Panel D by RSK residual controlling for RSJ.

Panel A. Sorted by RSJ Residual Controlling for REV

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	25.43	8.85	38.53	19.44
2	21.09	5.35	33.89	14.58
3	15.30	0.21	29.44	10.08
4	12.63	-2.87	26.55	7.27
5 (High)	6.63	-8.82	22.96	4.16
High−Low	-18.80	-17.67	-15.57	-15.27
	(-4.24)	(-4.00)	(-5.33)	(-5.35)

Panel B. Sorted by RSK Residual Controlling for REV

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	20.13	3.12	36.26	17.20
2	20.82	5.13	32.51	13.30
3	15.19	0.13	28.69	9.46
4	13.51	-1.96	28.24	8.84
5 (High)	13.92	-1.84	25.68	6.74
High−Low	-6.20	-4.96	-10.58	-10.45
	(-1.60)	(-1.27)	(-4.39)	(-4.42)

Panel C. Sorted by RSJ Residual Controlling for RSK

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	36.28	20.42	50.90	31.23
2	20.08	4.23	37.46	18.25
3	17.26	1.10	29.92	10.77
4	9.64	-5.80	22.89	4.01
5 (High)	-0.17	-15.70	17.49	-1.17
High−Low	-36.45	-36.11	-33.41	-32.40
	(-7.04)	(-7.11)	(-8.42)	(-8.50)

Panel D. Sorted by RSK Residual Controlling for RSJ

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1 (Low)	0.74	-14.89	21.49	2.86
2	10.55	-4.89	24.32	5.30
3	16.91	0.77	30.00	10.75
4	21.59	5.74	37.95	18.79
5 (High)	33.88	18.32	44.91	25.39
High−Low	33.14	33.22	23.42	22.53
	(6.61)	(6.71)	(7.05)	(7.04)

Panel B of Table 4 repeats this same analysis in which we sort the stocks into quintile portfolios according to the residuals from the weekly cross-sectional regressions of RSK on REV. Although the RSK sorts that control for REV still result in a weekly abnormal return spread of −10.45 bps, with a t-statistic of −4.42, for the equal-weighted portfolios, the spread for the value-weighted portfolios is reduced to only −4.96 bps, with an insignificant t-statistic of -1.27.[16] Taken together, the results in Panels A and B clearly suggest that RSJ contains more independent information beyond REV than does RSK.

This same residual-based sorting approach also allows us to assess the inherent predictability of the RSJ and RSK measures against each other, by sorting firms into portfolios based on the residuals from the weekly cross-sectional regressions of RSJ against RSK, or RSK against RSJ. The portfolio returns and FFC4 alphas obtained from sorting based on these RSJ residuals, orthogonal to RSK, are reported in Panel C of Table 4. The value- and equal-weighted portfolios both result in highly significant abnormal return spreads. The High$-$Low FFC4 alpha for the value-weighted portfolios, in particular, equals -36.11 bps with a t-statistic of -7.11, revealing an even stronger degree of predictability of the RSJ residual-based sorts, compared to the standard single sorts based on RSJ reported in Panel A of Table 3.

In sharp contrast, the sorts based on the RSK residuals orthogonal to RSJ fail to reproduce the same negative return predictability as the simple RSK sorts in Panel C of Table 3. Instead, the two FFC4 columns in Panel D show that the RSK residuals purged from the influence of RSJ strongly *positively* predict the cross-sectional variation in the future returns. The magnitudes of these return differences are not only highly statistically significant, but also economically large. For example, the weekly FFC4 alpha for the High$-$Low residual sorted value-weighted portfolios equals 33.22 bps, with a t-statistic of 6.71. These results cannot simply be ascribed to measurement errors in RSK, which would

[16] These results for the residual-based sorts are also in line with ACJV, who report much weaker t-statistics for the High$-$Low spread for the value-weighted RSK-sorted portfolios at different REV levels.

only diminish the negative relation between RSK and the future returns, but not change the sign. Instead, the results suggest that RSJ and RSK share a common component that accounts for their high contemporaneous correlation and the strong negative return predictability observed in the conventional single sorts reported in Table 3. However, once the influence of this common component, which manifests most strongly in the RSJ measure, is controlled for, the effect of the realized skewness is completely reversed. Appendix A.3 provides a more formal econometric rational for how this change of sign may arise in the data.

C. Double-Sorted Portfolios

The results from the standard single portfolio sorts and the single sorts with controls reported in Tables 3 and 4, respectively, reveal a strong negative relation between the relative signed jump variation and the future returns, which cannot be accounted for by the previously documented weekly reversal effect, nor the realized skewness effect. By contrast, the negative predictability of the realized skewness is considerably diminished after controlling for the weekly return reversals, and completely reversed after controlling for the relative signed jump variation. Another popular approach to control for the effect of other variables associated with the cross-sectional variation in returns is to rely on double portfolio sorts. Table 5 reports the results from a series of such sequential sorts in which we alternate between the ordering of the RSJ and RSK based sorts.[17]

[17]The Supplementary Material reports the results from additional double sorts based on these same two realized measures that first sort on other explanatory variables.

Table 5: **Predictive Double-Sorted Portfolios**

Table 5 reports the average 1-week ahead returns sorted by RSJ controlling for RSK, and vice versa. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between \$5 and \$1,000 over the 1993–2013 sample period. In Panel A, for each week, all stocks in the sample are first sorted into 5 quintiles on the basis of RSJ. Within each quintile, the stocks are then sorted into 5 quintiles according to RSK. For each 5 x 5 grouping, we form a value-weighted portfolio (left panel) and an equal-weighted portfolio (right panel). These 5 RSJ portfolios are then averaged across the 5 RSK portfolios to produce RSJ portfolios with large cross-portfolio variation in their RSJ but little variation in RSK. In Panel B, we reverse the order to first sort on RSK and then on RSJ. RSJ and RSK denote the relative signed jump and realized skewness. In Panel A/B, the first 5 rows in both value-weighted and equal-weighted sorting results report time-series averages of weekly excess returns for the RSJ/RSK quintile portfolios. The row labeled "High−Low" reports the difference in the returns between portfolio 5 and portfolio 1. The row labeled "FFC4" reports the average Fama–French–Carhart 4-factor alphas. The corresponding Newey–West robust t-statistics are reported in parentheses.

Panel A. Sorted by RSJ Controlling for RSK

	Value-Weighted							Equal-Weighted					
	RSK Quintiles							RSK Quintiles					
	1 (Low)	2	3	4	5 (High)	Average		1 (Low)	2	3	4	5 (High)	Average
1 (Low)	43.26	42.65	31.94	22.53	12.27	30.53	1 (Low)	64.95	54.17	42.42	39.72	27.46	45.74
2	31.71	24.93	12.49	16.50	16.22	20.37	2	57.93	44.39	32.62	30.75	25.65	38.27
3	33.14	22.66	15.39	6.74	6.10	16.81	3	53.13	33.66	26.91	22.26	20.41	31.27
4	26.02	18.48	10.13	8.40	-1.38	12.33	4	47.53	36.18	24.71	17.96	16.00	28.47
5 (High)	15.65	13.52	4.47	0.74	6.37	8.15	5 (High)	32.65	21.96	16.29	15.87	15.54	20.46
High−Low	-27.60	-29.13	-27.47	-21.79	-5.90	-22.38	High−Low	-32.30	-32.20	-26.13	-23.86	-11.92	-25.28
	(-4.16)	(-4.06)	(-4.19)	(-3.20)	(-0.92)	(-5.43)		(-7.31)	(-6.16)	(-5.09)	(-4.81)	(-2.74)	(-7.40)
FFC4	-26.01	-30.33	-25.90	-20.22	-4.48	-21.39	FFC4	-32.24	-31.55	-24.52	-22.83	-9.97	-24.22
	(-3.75)	(-4.26)	(-3.92)	(-2.95)	(-0.70)	(-5.16)		(-7.31)	(-6.16)	(-4.84)	(-4.73)	(-2.50)	(-7.38)

Panel B. Sorted by RSK Controlling for RSJ

	Value-Weighted							Equal-Weighted					
	RSJ Quintiles							RSJ Quintiles					
	1 (Low)	2	3	4	5 (High)	Average		1 (Low)	2	3	4	5 (High)	Average
1 (Low)	33.93	16.22	14.62	2.57	-1.98	13.07	1 (Low)	59.66	34.07	25.17	18.22	13.27	30.08
2	29.21	22.05	9.38	11.54	3.09	15.05	2	54.97	36.93	28.08	22.12	18.21	32.06
3	32.56	16.51	13.80	4.55	5.44	14.57	3	51.64	36.87	29.07	19.95	20.36	31.58
4	31.32	26.80	16.73	15.94	13.72	20.90	4	53.86	38.85	29.47	25.26	21.40	33.77
5 (High)	42.76	32.31	21.77	11.80	15.92	24.91	5 (High)	58.36	42.53	39.75	27.04	18.07	37.15
High−Low	8.83	16.09	7.15	9.24	17.91	11.84	High−Low	-1.30	8.46	14.58	8.82	4.80	7.07
	(1.27)	(2.70)	(1.19)	(1.55)	(3.26)	(3.50)		(-0.29)	(2.03)	(3.71)	(2.33)	(1.24)	(2.93)
FFC4	9.99	16.88	7.61	7.09	17.09	11.73	FFC4	-2.89	7.29	13.73	7.66	5.58	6.27
	(1.49)	(2.83)	(1.25)	(1.18)	(3.03)	(3.45)		(-0.68)	(1.76)	(3.55)	(2.02)	(1.42)	(2.63)

Panel A of Table 5, in particular, shows the results obtained by sorting on RSJ after first sorting on RSK. At the end of each Tuesday, we first sort all of the stocks into quintile portfolios based on their individual RSK measures. Within each of these characteristic portfolio, we then sort the stocks into quintiles based on their RSJ measure for that same week, and compute the returns over the subsequent week for the resulting 25 (5×5) portfolios. The row labelled "High$-$Low" reports the average return spread between these High and Low quintile portfolios within each RSK quintile, while the row labelled "FFC4" reports the return spreads adjusted by the four Fama–French–Carhart risk factors. To focus more directly on the effect of RSJ, we also compute the returns averaged across RSK quintiles as a way to produce quintile portfolios with large variations in RSJ, but small variations in RSK. These returns are reported in the last column labeled "Average."

The resulting FFC4 alpha for the difference in the value-weighted returns on the fifth and first RSJ quintile portfolios obtained by first sorting on RSK equals -21.39. This economically large spread also has a highly significant t-statistic of -5.16, again underscoring that RSK cannot explain the predictability of RSJ. Interestingly, looking at the RSJ effect within each of the RSK quintiles, shows that RSJ negatively predicts the future returns within four of the 5 quintiles. The equal-weighted double sorts exhibit even more significant patterns, both within and across RSK quintiles.

Panel B of Table 5 shows the results from similarly constructed sequential double sorts based on RSK in which we first sort on RSJ. The FFC4 alpha for the value-weighted portfolios given in the bottom right entry equals 11.73, with a t-statistic of 3.45, thus suggesting that RSK *positively* predicts future returns after controlling for RSJ. This positive predictability of RSK contradicts the strong negative predictability of RSK previously documented in ACJV and the single sorts in Panel C of Table 3. However, the results are consistent with the residual sorts reported in Panel D of Table 4 that control for the influence of RSJ.[18] Interestingly, this positive predictability of RSK after first sorting on RSJ holds true across *all* quintiles. The equal-weighted double sorts show the same positive return predictability patterns associated with RSK after first sorting on RSJ.

In sum, the negative relation between the future returns and the relative signed jump variation measure remains intact after controlling for the influence of the realized skewness. On the other hand, the tendency for high/low realized skewness to be associated with low/high future returns completely disappears, and even reverses, after controlling for the relative signed jump variation.

D. Firm-Level Cross-Sectional Regressions

The portfolio sorts discussed above ignore potentially important firm-level information by aggregating the stocks into quintile portfolios. Also, even though the single-sorted portfolios with controls and the double-sorted portfolios both allow for the possibility that more then one explanatory variable might be linked to the cross-sectional variation in the returns, they only control for one variable at a time. In an effort to further corroborate and expand on these results, this section reports the results from a series of standard Fama–MacBeth (1973) cross-sectional type regressions that simultaneously control for multiple explanatory variables.

[18] This again is also consistent with the idea that RSJ provides a more accurate proxy for some underlying latent factor that drives the returns, as discussed more formally in Appendix A.3.

Specifically, for each of the weeks in the sample, we run the following cross-sectional regressions,

$$r_{i,t+1} = \gamma_{0,t} + \sum_{j=1}^{K} \gamma_{j,t} Z_{j,i,t} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., N,$$

where $r_{i,t+1}$ denotes the return for stock i over week $t+1$ (Tuesday-close to Tuesday-close), and the K stock-specific control variables $Z_{j,i,t}$ are all measured at the end of week t. Having estimated the slope coefficients for each of the weeks in the sample, we compute the time-series averages of the $\hat{\gamma}_{j,t}$ estimates to assess whether the different controls are able to predict the future returns. Table 6 reports the resulting $\bar{\gamma}_j$ averages and corresponding t-statistics for a number of different specifications.

Table 6: **Fama-MacBeth Cross-Sectional Regressions**

Table 6 reports the estimated regression coefficients and robust t-statistics (in parentheses) from Fama-MacBeth cross-sectional regressions for weekly stock returns. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between \$5 and \$1,000 over the 1993–2013 sample period. RSJ, RVOL, RSK, and RKT denote the relative signed jump variation, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the standard CAPM beta. ME denotes the logarithm of the market capitalization of the firms. BM denotes the ratio of the book value of common equity to the market value of equity. MOM is the compound gross return from day $t-252$ through day $t-21$. REV is the lagged 1-week return. IVOL is a measure of idiosyncratic volatility. CSK and CKT are measures of coskewness and cokurtosis, respectively. MAX and MIN represent the maximum and minimum daily raw returns over the previous week. ILLIQ refers to the natural logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the previous week. Panel A reports the results of simple regressions with a single explanatory variable. Panel B reports the results of multiple regressions with more than one explanatory variable.

Panel A. Simple Regressions

	RSJ	RVOL	RSK	RKT	BETA	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
	-111.76	6.01	-21.47	-0.31	2.73	-2.49	4.28	0.00	-0.02	-58.97	2.09	1.48	-0.02	-0.02	0.37
	(-8.20)	(0.44)	(-7.97)	(-0.70)	(0.32)	(-1.44)	(0.85)	(1.31)	(-5.87)	(-0.25)	(0.34)	(0.51)	(-2.78)	(-1.64)	(0.87)

Panel B. Multiple Regressions

Regression	RSJ	RVOL	RSK	RKT	BETA	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
I	-74.29				-0.24	-4.28	-0.39	0.00	-0.03	-198.27	-4.43	1.92	0.02	0.03	-0.77
	(-9.17)				(-0.04)	(-3.35)	(-0.14)	(2.14)	(-7.20)	(-1.50)	(-1.03)	(0.89)	(3.32)	(5.64)	(-2.74)
II		1.78			-1.06	-4.23	-0.34	0.00	-0.03	-211.07	-4.65	2.02	0.02	0.04	-0.85
		(0.26)			(-0.16)	(-3.44)	(-0.12)	(2.16)	(-9.07)	(-1.71)	(-1.09)	(0.94)	(3.69)	(6.05)	(-2.97)
III			-12.60		0.08	-4.37	-0.40	0.00	-0.03	-190.68	-4.51	1.84	0.02	0.03	-0.79
			(-7.33)		(0.01)	(-3.41)	(-0.15)	(2.15)	(-8.14)	(-1.44)	(-1.05)	(0.85)	(3.54)	(5.82)	(-2.80)
IV				-0.78	0.30	-4.55	-0.83	0.00	-0.03	-188.95	-4.35	1.90	0.02	0.03	-0.81
				(-2.37)	(0.04)	(-3.50)	(-0.30)	(2.21)	(-9.12)	(-1.43)	(-1.01)	(0.88)	(3.83)	(5.91)	(-2.87)
V	-248.78	1.16	34.62	-0.49											
	(-8.57)	(0.08)	(6.31)	(-1.02)											
VI	-255.02	-12.96	35.20	-1.07	-2.34	-3.46	0.38	0.00							
	(-10.50)	(-1.58)	(7.42)	(-2.92)	(-0.34)	(-2.75)	(0.14)	(1.68)							
VII	-184.93	-11.54	25.57	-1.08	-1.00	-3.44	0.32	0.00	-0.01						
	(-8.34)	(-1.44)	(5.65)	(-2.98)	(-0.15)	(-2.76)	(0.12)	(1.68)	(-4.41)						
VIII	-254.27	-6.84	35.02	-0.98	-1.62	-3.93	-0.56	0.00		-308.17					
	(-10.49)	(-0.90)	(7.37)	(-2.67)	(-0.24)	(-3.12)	(-0.21)	(1.87)		(-2.87)					
IX	-248.79	-13.03	34.22	-1.04	-2.37	-3.46	0.52	0.00			0.37				
	(-10.34)	(-1.61)	(7.25)	(-2.86)	(-0.35)	(-2.75)	(0.19)	(1.74)			(0.10)				
X	-249.16	-12.57	34.25	-1.10	-2.97	-3.63	0.39	0.00				1.83			
	(-10.38)	(-1.52)	(7.27)	(-3.00)	(-0.45)	(-2.87)	(0.14)	(1.77)				(1.12)			
XI	-235.83	-7.16	32.29	-0.91	-1.49	-3.19	0.23	0.00					-0.01		
	(-9.86)	(-0.86)	(6.79)	(-2.48)	(-0.22)	(-2.56)	(0.08)	(1.75)					(-3.42)		
XII	-255.32	-11.84	35.16	-1.01	-2.86	-3.29	0.46	0.00						0.00	
	(-11.12)	(-1.46)	(7.68)	(-2.75)	(-0.43)	(-2.61)	(0.17)	(1.72)						(0.55)	
XIII	-247.02	-12.75	34.02	-1.05	-2.37	-4.30	0.47	0.00							-0.84
	(-10.19)	(-1.56)	(7.17)	(-2.87)	(-0.35)	(-3.41)	(0.17)	(1.67)							(-2.92)
XIV	-159.73	-1.32	21.46	-0.84	-1.36	-4.31	-0.21	0.00	-0.02	-203.76	-4.31	2.20	0.02	0.03	-0.80
	(-7.50)	(-0.18)	(4.83)	(-2.31)	(-0.21)	(-3.48)	(-0.08)	(2.22)	(-6.62)	(-1.66)	(-1.02)	(1.03)	(3.25)	(5.62)	(-2.92)

Panel A of Table 6, in particular, focuses on simple regressions, in which we regress the returns against a single explanatory variable at a time. Consistent with the results for the single-sorted portfolios, RSJ and RSK both negatively predict the subsequent weekly returns, with highly statistically significant t-statistics of -8.20 and -7.97, respectively. In addition, REV stands out as the only other explanatory variable with a clearly significant t-statistic. The estimated slope coefficients for the other explanatory variables generally also have the "correct" sign, but with the exception of MAX none of the other variables are significant at the 5% level.

Turning to Panel B of Table 6, and the multiple regressions that simultaneously control for more than one variable at a time, the relative signed jump variation RSJ is always highly significant. Putting the estimates into perspective, the average cross-sectional standard deviation of RSJ equals 0.16. Hence, the average slope of -159.73 in the last Regression XIV that includes all of the variables implies that a 2-standard-deviation decrease in RSJ predicts a rise of approximately 26% in the annual returns ($2 \times 159.73 \times 0.16/10,000 \times 52 = 26\%$). Thus, not only is the predictability afforded by RSJ highly statistically significant, it is also highly significant economically.

The realized kurtosis RKT also negatively predicts the future returns across all of the different specifications. However, the level of significance is much lower than for RSJ. By contrast, the realized skewness, which consistent with the prior empirical evidence in ACJV, negatively predicts the future returns in the simple regression in Panel A of Table 6 and Regression III in Panel B, *positively* predicts the future returns in all of the regressions that include RSJ as a control. This, of course, mirrors the findings based on the double sorts discussed in Section V, and further highlights the fragility of RSK as a predictor.

VI. Dissecting RSJ-Based Portfolio Strategies

The results in the previous section naturally raise the questions of where the superior performance of the RSJ-based portfolio strategies are coming from? And whether the resulting "paper portfolio" profits are somehow linked to the informational environment and costs of trading? This section provides some partial answers to these questions.

A. RSJ Profitability and Other Control Variables

We begin by examining how the performance of the RSJ-sorted portfolios vary across firm size, volatility, illiquidity and return reversal. The first three variables, in particular, are often used to assess how anomalies are affected by the informational environment and trading costs more generally. The mechanics behind these additional double sorts, reported in Table 7, closely mirrors those discussed in Section V. The only difference is that to more explicitly highlight the impact of a given control variable, we report the differences in the value-weighted return spreads between the High- and Low-level of the specific control variable, rather than the averages across these levels.

Table 7: **RSJ Portfolios Sorted on Control Variables**

Table 7 reports the performance of portfolios sorted by RSJ and control variables. The sample consists of all the NYSE, AMEX, and NASDAQ listed common stocks with share codes 10 or 11 and prices between \$5 and \$1,000 over the 1993–2013 sample period. In each panel, for each week, all stocks in the sample are first sorted into 5 quintiles on the basis of 1 control variable. Within each quintile, the stocks are then sorted into 5 quintiles according to their RSJ. For each 5 x 5 grouping, we form an value-weighted portfolio. Then we consider the performance of the 25 portfolios from the intersection of the double sorts. RSJ and RVOL denote the relative signed jump and realized volatility. ME denotes the natural logarithm of the market capitalization of the firms. ILLIQ refers to the natural logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the previous week. REV denotes the lagged 1-week return. In each panel, the 5 rows/columns labeled as 1–5 represent 5 levels of RSJ/the control variable. The row/column labeled "High−Low" reports the difference in value-weighted returns between Portfolio 5 and Portfolio 1 constructed according to RSJ/the control variable. The row labeled "FFC4" reports the Fama–French–Carhart 4-factor alphas. The corresponding Newey–West robust t-statistics are reported in parentheses.

Panel A. ME

Value-Weighted

	ME Quintiles					
	1 (Low)	2	3	4	5 (High)	High−Low
1 (Low)	87.76	49.93	37.02	33.91	29.52	-58.24
2	77.56	41.65	26.52	25.40	21.38	-56.18
3	52.43	30.19	21.03	21.38	16.17	-36.27
4	37.24	23.70	15.20	15.38	7.06	-30.17
5 (High)	28.34	15.43	13.21	12.92	2.13	-26.21
High−Low	-59.42	-34.49	-23.80	-20.99	-27.39	32.03
	(-10.19)	(-6.69)	(-4.87)	(-4.07)	(-5.22)	(4.64)
FFC4	-59.16	-33.47	-22.96	-20.63	-26.67	32.49
	(-10.35)	(-6.68)	(-4.75)	(-3.94)	(-5.03)	(4.76)

Panel B. RVOL

Value-Weighted

	RVOL Quintiles					
	1 (Low)	2	3	4	5 (High)	High−Low
1 (Low)	30.01	29.13	36.67	43.08	75.91	45.89
2	20.74	25.44	22.97	25.20	45.04	24.30
3	13.84	16.21	14.68	27.89	37.20	23.36
4	8.61	11.54	7.22	4.54	14.69	6.07
5 (High)	3.86	3.13	4.32	-2.50	5.62	1.76
High−Low	-26.15	-26.00	-32.35	-45.58	-70.29	-44.13
	(-5.95)	(-3.98)	(-3.98)	(-5.07)	(-6.73)	(-4.06)
FFC4	-26.07	-26.21	-31.59	-46.10	-70.16	-44.09
	(-6.05)	(-3.91)	(-3.84)	(-5.16)	(-6.62)	(-4.09)

Panel C. ILLIQ

Value-Weighted

	ILLIQ Quintiles					
	1 (Low)	2	3	4	5 (High)	High−Low
1 (Low)	30.55	39.45	35.83	37.65	67.30	36.75
2	24.67	26.78	23.37	28.13	41.79	17.12
3	14.20	20.49	19.52	24.04	27.62	13.42
4	8.06	15.25	18.54	16.16	17.81	9.75
5 (High)	2.66	10.45	14.21	14.40	4.99	2.32
High−Low	-27.89	-29.00	-21.61	-23.25	-62.31	-34.42
	(-4.82)	(-5.48)	(-3.97)	(-4.58)	(-9.83)	(-4.65)
FFC4	-27.61	-28.09	-21.47	-22.26	-61.62	-34.02
	(-4.76)	(-5.20)	(-3.96)	(-4.44)	(-10.03)	(-4.64)

Panel D. REV

Value-Weighted

	REV Quintiles					
	1 (Low)	2	3	4	5 (High)	High−Low
1 (Low)	52.82	30.38	23.30	11.84	6.68	-46.14
2	49.06	27.89	19.45	7.57	-3.98	-53.04
3	40.02	26.30	14.18	2.01	-1.08	-41.11
4	39.99	24.39	17.69	6.58	-11.64	-51.63
5 (High)	28.14	17.24	13.04	2.81	-12.81	-40.95
High−Low	-24.68	-13.14	-10.26	-9.03	-19.49	5.19
	(-2.98)	(-2.05)	(-1.73)	(-1.50)	(-2.65)	(0.48)
FFC4	-22.88	-12.41	-10.52	-6.99	-18.95	3.93
	(-2.72)	(-1.93)	(-1.76)	(-1.20)	(-2.63)	(0.37)

Panel A of Table 7 shows that the RSJ strategy tends to be more profitable for smaller stocks. For the value-weighted portfolios, the weekly 4-factor alpha of the RSJ strategies equals −59.16 bps for small firms compared to −26.67 bps for large firms, with t-statistics of −10.35 and −5.03, respectively. Also, the difference in the alphas between small and large firms equals 32.49 bps per week, with a highly statistically significant t-statistic of 4.76. These results are consistent with the idea that large firms tend to have better information environments and more sophisticated traders, resulting in less overreaction to extreme price movements, and thus weaker RSJ effects.

Panel B of Table 7 examines RSJ portfolios for different volatility levels. For the value-weighted portfolios, the 4-factor alpha for the RSJ strategy equals −26.07 bps per week for the least volatile quantile, compared to −70.16 bps for the most volatile quantile. Also, the difference in the 4-factor alphas between the two groups is −44.09 bps per week, with a t-statistic of −4.09. Assuming that firms with more volatile stock prices exhibit greater informational asymmetries, arbitrage risks may thus help explain the more pronounced RSJ effects for more volatile firms.

Panel C of Table 7 relies on the Amihud illiquidity measure to assess the effect of trading costs. The results indicate a stronger RSJ effect for stocks that are more costly to trade. For the bottom quintile of stocks with the lowest illiquidity measure, the 4-factor alpha of the RSJ strategy equals −27.61 bps per week, with a t-statistic of −4.76, whereas for the top quintile of stocks with the highest illiquidity measure, the 4-factor alpha is −61.62 bps, with a t-statistic of −10.03. Moreover, the difference in the 4-factor alphas equals −34.02 bps per week, with a t-statistic of −4.64. Since illiquid stocks are more costly and risky to trade, these results indirectly support the notion that limits to arbitrage prevent traders from betting against perceived mispricing (see, e.g., Shleifer and Vishny (1997)), and why the RSJ effect is the strongest for the most difficult to trade stocks.

The last Panel D of Table 7 further examines the interaction between the RSJ and reversal strategies. The weekly 4-factor alpha of the RSJ strategies equals −22.88 bps for the firms with the lowest lagged 1-week returns, compared to −18.95 for the firms with highest lagged 1-week returns, with t-statistics of −2.72 and −2.63, respectively. The difference in the alphas between low and high REV firms equals 3.93 bps per week, with an insignificant t-statistic of 0.37. The smaller FFC4 alphas for the RSJ strategies across REV quantiles indicates once again that part of the predictability of RSJ is attributable to the short-term reversal effect.

B. Autocovariances and RSJ Profits

To help further understand where the profits obtained by buying low-RSJ stocks and selling high-RSJ stocks is coming from, we follow Lo and MacKinlay (1990) and decompose the cross-sectional predictability from an RSJ-based strategy into three sources: autocorrelations in the returns, lead-lag relations among the different stocks, and cross-sectional dispersion in the unconditional mean returns.

Specifically, consider the zero-cost portfolio with weights determined by the relative magnitude of the individual stocks' RSJ,

$$w_{i,t} = \frac{1}{c_t}(\mathrm{RSJ}_{i,t} - \mathrm{RSJ}_{m,t}), \tag{11}$$

where $c_t = (\sum\limits_{i=1}^{N} |\mathrm{RSJ}_{i,t} - \mathrm{RSJ}_{m,t}|)/2$ denotes a scaling factor, and $\mathrm{RSJ}_{m,t} = \sum\limits_{i=1}^{N} \mathrm{RSJ}_{i,t}/N$ equals the average RSJ for week t. The scaling factor c_t ensures that the strategy is always \$1 long and \$1 short so that the magnitude of the profits are easily interpretable (see, e.g., the discussions in Lehmann (1990), Nagel (2012)). Let π_{t+1} denote the week $t+1$ profit on the portfolio,

$$\pi_{t+1} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1} = \frac{1}{c_t} \sum_{i=1}^{N} (\mathrm{RSJ}_{i,t} - \mathrm{RSJ}_{m,t}) r_{i,t+1}. \tag{12}$$

Then, following Lo and MacKinlay (1990), the expected profit is naturally decomposed into three separate terms,

$$\mathrm{E}(\pi_{t+1}) = \frac{N-1}{N^2} \mathrm{tr}(\Gamma) - \frac{1}{N^2} [1'\Gamma 1 - \mathrm{tr}(\Gamma)] + \sigma^2_{\mu_{\mathrm{RSJ}}, \mu_R}, \tag{13}$$

where $\Gamma = \mathrm{cov}(N/c_t \times \mathrm{RSJ}_t, R_{t+1})$ for $\mathrm{RSJ}_t \equiv (\mathrm{RSJ}_{1,t}, \mathrm{RSJ}_{2,t}, \ldots, \mathrm{RSJ}_{N,t})'$, $R_{t+1} \equiv (r_{1,t+1}, r_{2,t+1}, \ldots, r_{N,t+1})'$ denotes the covariance between the scaled RSJ in week t and the return in week $t+1$, while $\sigma^2_{\mu_{\mathrm{RSJ}}, \mu_R}$ denotes the cross-sectional covariance between the unconditionally expected RSJ and the future returns. The first term in equation (13), $(N-1)\mathrm{tr}(\Gamma)/N^2$, represents the average autocovariance of the individual stocks. It would be positive/negative if low RSJ stocks became future losers/winners. The second term, $-[1'\Gamma 1 - \mathrm{tr}(\Gamma)]/N^2$, gives the average cross-serial covariance. It would be postive/negative if firms with high RSJ predict low/high future returns of other firms. Lastly, the third cross-sectional covariance term, $\sigma^2_{\mu_{\mathrm{RSJ}}, \mu_R}$, would be postive/negative if firms with high unconditional RSJ also have high/low unconditional returns.

Table 8 reports the unconditional sample values for the three separate terms based on the stocks with complete return and RSJ histories, along with the corresponding robust standard errors. Panel A gives the results for the raw returns, while Panel B gives the results for the FFC4-adjusted returns. The findings are generally consistent with an overreaction-based explanation. The total profit based on the raw returns equals -23.56 bps per week, with a t-statistic of -7.87, while the FFC4-adjusted returns produce a profit of -25.55 bps, with a t-statistic of -10.55. Most of this profitability is attributable to the autocovariance component, which generates a weekly profit of -30.02 bps, with a t-statistic of -4.07, for the raw returns, and a FFC4 alpha of -28.24, with a t-statistic of -10.68. By comparison, the cross-serial component equals just 5.87 bps, with a t-statistic of 1.00, for the raw returns, and 2.24 bps for the FFC4 alpha, with a t-statistic of 1.98. The unconditional covariance components are nearly 0. In other words, the profitability arises from variation in the stock's own RSJ, not other stocks' RSJ, suggestive of an overreaction to large and sudden price moves.

Table 8: **High−Low Portfolio Profit Decomposition**

Table 8 reports the Lo–MacKinlay (1990) decomposition of the High−Low portfolio profit based on RSJ, for the 856 stocks that have complete return histories over the 1993–2013 sample period. The column labeled "Auto" gives the profit attributable to the autocovariance component; "Cross" is the profit attributable to the cross-serial covariance component; "Mean" is the component attributable to the cross-sectional covariance between the unconditional expected RSJ and the overall returns; and "Total" refers to the total profit. Panel A reports the component profits based on raw returns. Panel B reports the component profits based on Fama–French–Carhart 4-factor adjusted residual returns. Newey–West robust t-statistics are reported in parentheses.

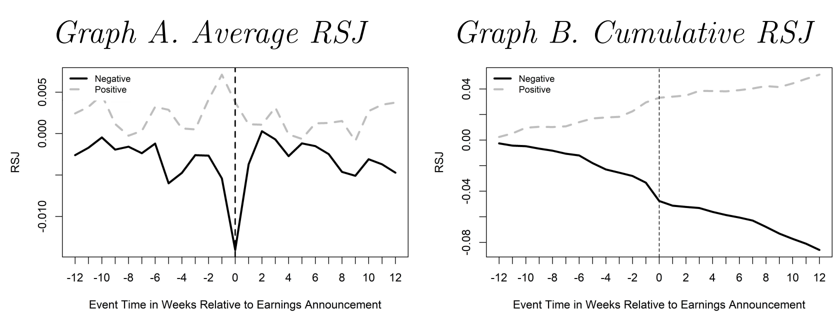
Panel A. Raw Return				*Panel B. FFC4*			
Auto	Cross	Mean	Total	Auto	Cross	Mean	Total
-30.02	5.87	0.59	-23.56	-28.24	2.24	0.45	-25.55
(-4.07)	(1.00)		(-7.87)	(-10.68)	(1.98)		(-10.55)

C. RSJ and News Announcements

Do the "jumps" captured by RSJ, and the corresponding trading profits documented above, correspond to readily identifiable corporate events and/or firm-specific news? In an effort to ascertain whether they do, we follow the literature on post-earnings-announcement drifts (e.g., Bernard and Thomas (1989)), and plot the typical evolution of the RSJ measure around earnings announcements. Specifically, for each week in the sample, we compute the average and cumulative RSJ in the $[-12, 12]$ week window surrounding the announcement week conditional on positive and negative earnings surprises, respectively. The resulting averages depicted in Figure 4 reveal a clear positive "jump" in the RSJ measure 1 week prior to the announcement for positive earnings surprises, along with a negative "jump" in RSJ during the actual announcement week for negative surprises. Moreover, consistent with the extant literature and the well established pre- and post-announcement drifts (see, e.g., Fig. 1 of Bernard and Thomas (1989)), there are clear pre- and post-announcement trends evident in the cumulative RSJ measures as well.

Fig. 4: **RSJ Around Earnings**

Graph A of Figure 4 shows the average weekly RSJ in a $[-12, 12]$ week window surrounding positive and negative earnings surprise, respectively. Graph B shows the cumulative RSJ.



Meanwhile, it is important to recognize that the differences in returns associated with RSJ is not merely restricted to the time around earnings announcements. Indeed, many other, both public macroeconomic and firm specific news announcements, similarly manifest in the form of firm specific jumps and in turn large (in an absolute sense) RSJs (see, e.g., Lee (2012) and the discussion therein). Related to this, Savor and Wilson (2014) have also recently argued that cross-sectional return patterns are different on news announcement days.

VII. Conclusion

We document that firms with relatively high/low "good" minus "bad" volatilities, constructed from the summation of high-frequency intraday positive and negative squared returns, respectively, are associated with low/high future returns. Sorting stocks into portfolios based on their individual relative signed jump variation results in an economically large value-weighted weekly return spread between the stocks in the lowest and highest quintile portfolios of 29.35 bps, or approximately 15% per year. The corresponding t-statistic of 5.83 also far exceeds the hurdle rate for judging cross-sectional return predictability recently advocated by Harvey et al. (2015). Adjusting the returns for the influence of the Fama–French–Carhart systematic risk factors hardly changes the magnitude of this return spread, nor its statistical significance. The return spreads also remain highly statistically significant and economically large in equal-weighted portfolios, double-sorted portfolios and Fama–MacBeth type regressions that control for other firm characteristics and explanatory variables previously associated with the cross-sectional variation in expected stock returns. By contrast, the negative predictability of the realized skewness measure recently documented by ACJV, is completely reversed after controlling for the relative "good" minus "bad" realized volatility.

Our empirical findings raise the question of why the firm specific relative signed variation so strongly predicts the future returns? Following the arguments in Breckenfelder and Tédongap (2012) and Farago and Tédongap (2018), it is possible that investors with disappointment aversion rationally price downside volatility more dearly than upside volatility, in turn resulting in a priced systematic downside volatility factor. Empirically, however, it remains to be seen whether the strong predictability afforded by the individual firms' high-frequency-based realized volatility measures can be accounted for by a common systematic priced risk factor. Also, the return predictability, albeit highly statistically significant at the weekly level, is relatively short-lived, dissipating over longer monthly horizons, casting some doubt on a purely risk-based explanation. Instead, the differential pricing of the firm specific "good" versus "bad" volatilities might reflect behavioral biases, stemming from overreaction to large sudden price declines, or negative "jumps." Further along these lines, we find that the predictability of RSJ is stronger among small firms, firms with more volatile stock prices and more illiquid firms, consistent with investor overreaction to extreme price movements and limits to arbitrage. We leave it for future research to more clearly delineate the roles played by these competing explanations.

Appendix

A.1 High-Frequency Data Cleaning

We begin by removing entries that satisfy at least one of the following criteria: a time stamp outside the exchange open window between 9:30 am and 4:00 pm; a price less than or equal to 0; a trade size less than or equal to 0; corrected trades, that is, trades with Correction Indicator, CORR, other than 0, 1, or 2; and an abnormal sale condition, that is, trades for which the Sale Condition, COND, has a letter code other than @, *, E, F, @E, @F, *E and *F. We then assign a single value to each variable for each second within the 9:30 am–4:00 pm time interval. If one or multiple transactions have occurred in that second, we calculate the sum of volumes, the sum of trades, and the volume-weighted average price within that second. If no transaction has occurred in that second, we enter 0 for volume and trades. For the volume-weighted average price, we use the entry from the nearest previous second. Motivated by our analysis of the trading volume distribution across different exchanges over time, we purposely incorporate information from all exchanges covered by the TAQ database.

A.2 Additional Explanatory Variables

Our empirical investigations rely on the following explanatory variables and firm characteristics.

- Size (ME): Following Fama and French (1993), a firm's size is measured by its market value of equity – the product of the closing price and the number of shares outstanding (in millions of dollars). Market equity is updated daily and is used to explain returns over the subsequent week. Following common practice, we also transform the size variable by its natural logarithm to reduce skewness.

- Book-to-market ratio (BM): Following Fama and French (1993), the book-to-market ratio in June of year t is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$. Book common equity is defined as book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus book value of preferred stock for fiscal year $t-1$.

- Momentum (MOM): Following Jegadeesh and Titman (1993), the momentum variable at the end of day t is defined as the compound gross return from day $t-252$ through day $t-21$; i.e., skipping the short-term reversal month.

- Reversal (REV): Following Jegadeesh (1990), Lehmann (1990) and ACJV (2016), the short-term reversal variable is defined as the weekly return over the previous week from Tuesday to Monday.

- Idiosyncratic volatility (IVOL): Following Ang et al. (2006b), a firm's idiosyncratic volatility at the end of day t is computed as the standard deviation of the residuals from the regression based on the daily returns between day $t-20$ and day t:

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i(r_{0,d} - r_{f,d}) + \gamma_i \mathrm{SMB}_d + \phi_i \mathrm{HML}_d + \epsilon_{i,d}, \tag{A.1}$$

where $r_{i,d}$ and $r_{0,d}$ are the daily returns of stock i and the market portfolio on day d, respectively, and SMB_d and HML_d denote the daily Fama and French (1993) size and book-to-market factors.

- Coskewness (CSK): Following Harvey and Siddique (2000) and Ang et al. (2006a), the coskewness of stock i at the end of day t is estimated using daily returns between day $t-20$ and day t as

$$\text{(A.2)} \qquad \widehat{\text{CSK}_{i,t}} = \frac{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)(r_{0,d}-\bar{r}_0)^2}{\sqrt{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)^2}\left(\frac{1}{N}\sum_d (r_{0,d}-\bar{r}_0)^2\right)},$$

  where N denotes the number of trading days, $r_{i,d}$ and $r_{0,d}$ are the daily returns of stock i and the market portfolio on day d, respectively, and $\bar{r}_i$ and $\bar{r}_0$ denote the corresponding average daily returns.

- Cokurtosis (CKT): Following Ang et al. (2006a), the cokurtosis of stock i at the end of day t is estimated using the daily returns between day $t-20$ and day t as

$$\text{(A.3)} \qquad \widehat{\text{CKT}_{i,t}} = \frac{\frac{1}{N}\sum\limits_d (r_{i,d}-\bar{r}_i)(r_{0,d}-\bar{r}_0)^3}{\sqrt{\frac{1}{N}\sum\limits_d (r_{i,d}-\bar{r}_i)^2}\left(\frac{1}{N}\sum\limits_d (r_{0,d}-\bar{r}_0)^2\right)^{3/2}},$$

  where variables are the same as for CSK.

- Maximum daily return (MAX): Following Bali et al. (2011) and ACJV (2016), the MAX variable is defined as the largest total daily raw return observed over the previous week.

- Minimum daily return (MIN): Following Bali et al. (2011) and ACJV (2016), the MIN variable is defined as the smallest total daily raw return observed over the previous week.

- Illiquidity (ILLIQ): Following Amihud (2002), the illiquidity for stock i at the end of day t is measured as the average daily ratio of the absolute stock return to the dollar trading volume from day $t-4$ through day t:

$$\text{ILLIQ}_{i,t} = \frac{1}{N} \sum_{d} \left(\frac{|r_{i,d}|}{\text{volume}_{i,d} \times \text{price}_{i,d}} \right), \tag{A.4}$$

  where $\text{volume}_{i,d}$ is the daily trading volume, $\text{price}_{i,d}$ is the daily price, and other variables are as defined before. We further transform the illiquidity measure by its natural logarithm to reduce skewness.

A.3 Change of Sign of RSK

To understand how the predictability of RSK changes sign (from significantly negative to significantly positive) after controlling for RSJ, consider the following data generating process (for simplicity and without loss of generality we assume the mean return to be zero),

$$r_{t+1} = aA_t + e_{t+1}, \tag{A.5}$$

$$\text{RSJ}_t = bA_t + u_t, \tag{A.6}$$

$$\text{RSK}_t = cA_t + v_t, \tag{A.7}$$

where r_{t+1} denotes the return for week $t+1$, and A_t denotes a latent common factor with zero mean and unit variance. Further assume that $a < 0$ (since the latent variable A negatively predicts future returns), and $b > 0$ and $c > 0$ (since RSJ and RSK both provide "noisy" proxies for the latent predictor variable). Now consider the joint regression,

$$r_{t+1} = \gamma_1 \mathrm{RSJ}_t + \gamma_2 \mathrm{RSK}_t + \epsilon_{t+1}. \tag{A.8}$$

The OLS estimates of $(\gamma_1, \gamma_2)'$ may be succinctly expressed as,

$$\begin{aligned} \begin{pmatrix} \hat{\gamma}_1 \\ \hat{\gamma}_2 \end{pmatrix} &= \begin{pmatrix} \sigma^2_{\mathrm{RSJ}} & \rho\sigma_{\mathrm{RSJ}}\sigma_{\mathrm{RSK}} \\ \rho\sigma_{\mathrm{RSJ}}\sigma_{\mathrm{RSK}} & \sigma^2_{\mathrm{RSK}} \end{pmatrix}^{-1} \times \begin{pmatrix} Cov(\mathrm{RSJ}_t, r_{t+1}) \\ Cov(\mathrm{RSK}_t, r_{t+1}) \end{pmatrix} \\ &= \frac{ab}{\sigma^2_{\mathrm{RSJ}}\sigma^2_{\mathrm{RSK}}(1-\rho^2)} \begin{pmatrix} \sigma_{\mathrm{RSK}}(\sigma_{\mathrm{RSK}} - \frac{c}{b}\rho\sigma_{\mathrm{RSJ}}) \\ \sigma_{\mathrm{RSJ}}(\frac{c}{b}\sigma_{\mathrm{RSJ}} - \rho\sigma_{\mathrm{RSK}}) \end{pmatrix}, \end{aligned} \tag{A.9}$$

where all of the right-hand-side variables refer to the corresponding sample analogues. Thus, the $\hat{\gamma}_2$ estimate will be positive if ρ and σ_{RSK} are sufficiently large. To put it differently, let $R^2_{\mathrm{RSJ}} = b^2/\sigma^2_{\mathrm{RSJ}}$ and $R^2_{\mathrm{RSK}} = c^2/\sigma^2_{\mathrm{RSK}}$ denote the R^2s from the respective univariate (latent) regressions of RSJ and RSK on A. The $\hat{\gamma}_2$ estimate will be positive when $R^2_{\mathrm{RSK}}/R^2_{\mathrm{RSJ}} < \rho^2$, or whenever RSJ provides a sufficiently more accurate proxy (as measured by the R^2) for the latent predictor variable than RSK.

Translating this to the actual data, equations (A.6) and (A.7) readily imply that,

$$\mathrm{RSK}_t = \frac{c}{b}\mathrm{RSJ}_t + w_t. \tag{A.10}$$

Correspondingly, regressing the weekly RSK on RSJ results in an estimate of $\widehat{\frac{c}{b}} = 4.19$. Moreover, $\sigma_{\text{RSK}} - \frac{c}{b}\rho\sigma_{\text{RSJ}} = 0.77 - 4.19 * 0.93 * 0.16 = 0.15 > 0$ and $\frac{c}{b}\sigma_{\text{RSJ}} - \rho\sigma_{\text{RSK}} = 4.19 * 0.16 - 0.93 * 0.77 = -0.05 < 0$, which by the above reasoning implies that $\hat{\gamma}_1 < 0$ and $\hat{\gamma}_2 > 0$, consistent with the observed change of sign for RSK from negative to positive between the simple and multiple return regressions.

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Supplementary Material to:

Good Volatility, Bad Volatility, and the Cross-Section of Stock Returns

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A-1. The Distribution of Realized Moments

Fig. A.1: Realized Measures Sorted by REV.
Panels A-D display the 10-week moving average time series of the RSJ, RVOL, RSK and RKT realized measures within REV terciles.

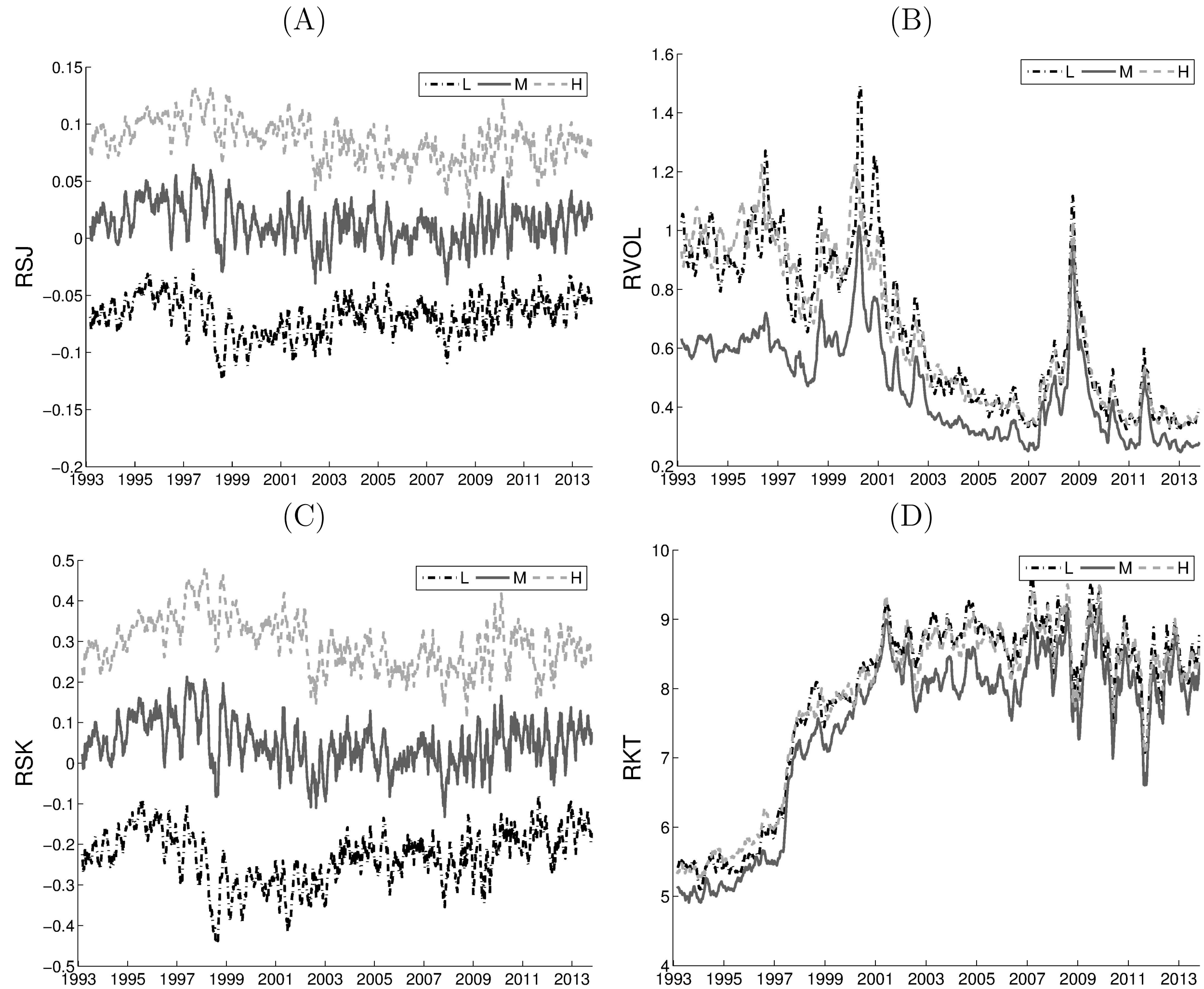


Fig. A.2: Realized Measures Sorted by RSJ.

Panels A-D display the 10-week moving average time series of the RSJ, RVOL, RSK and RKT realized measures within RSJ terciles.

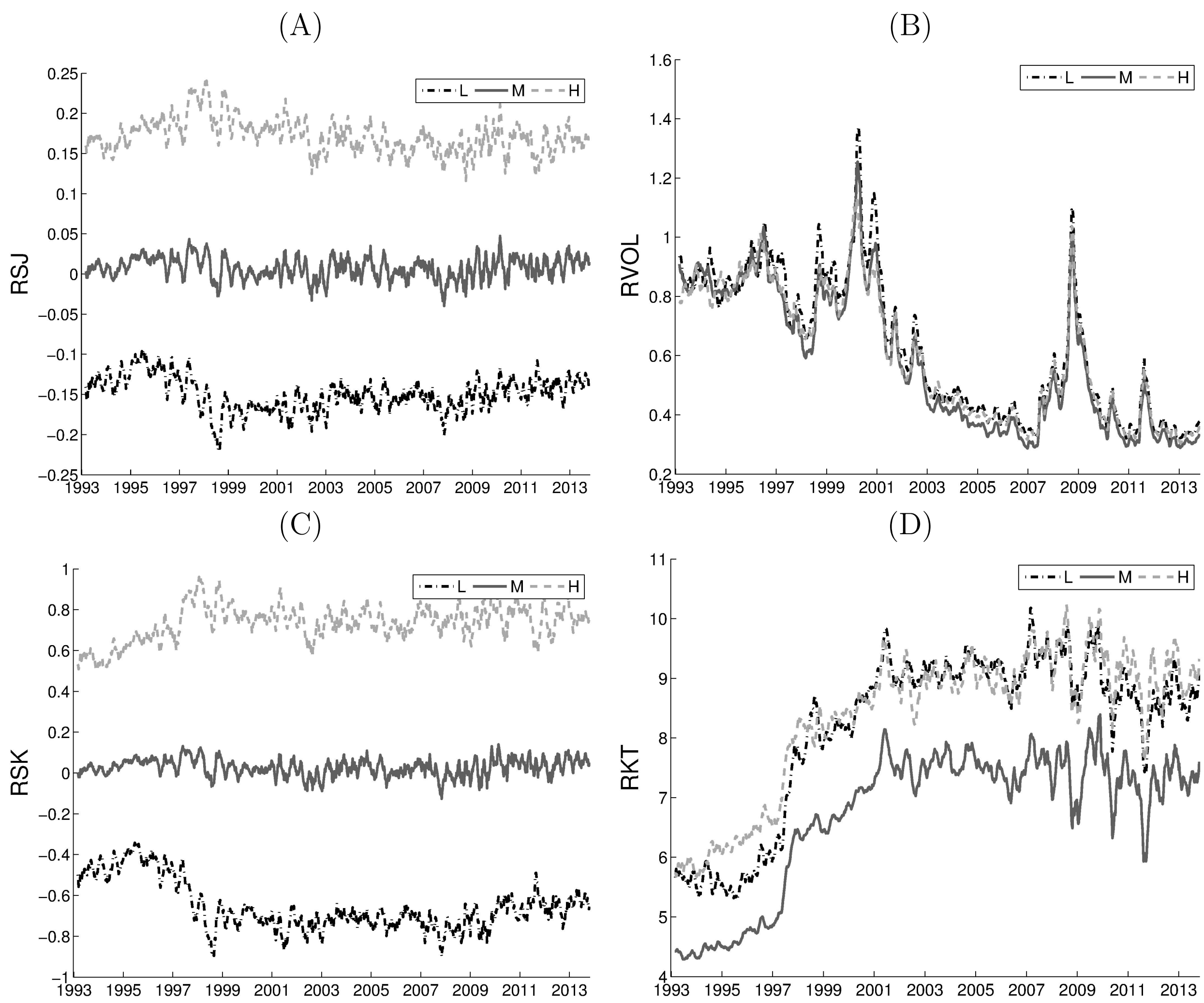
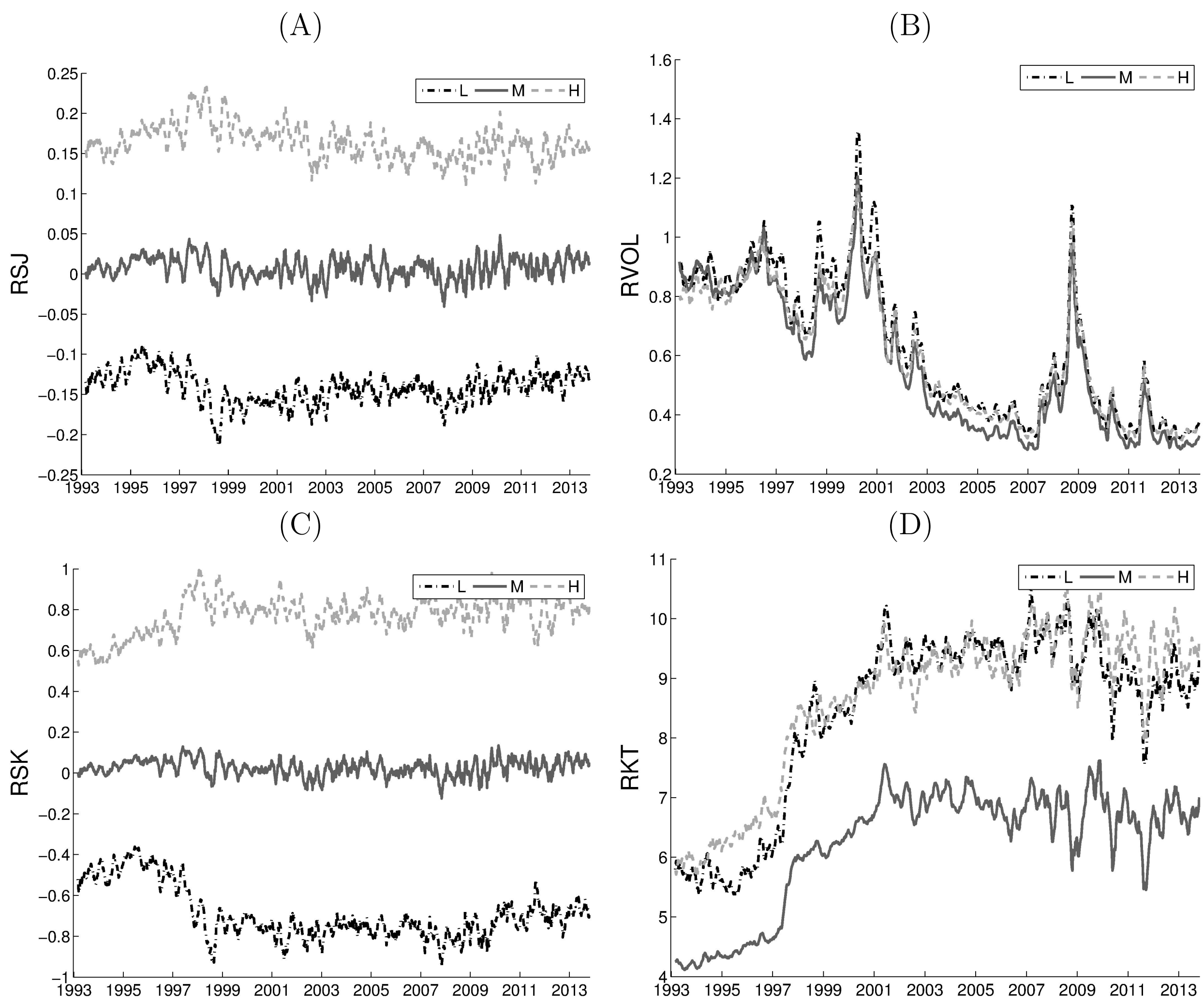


Fig. A.3: Realized Measures Sorted by RSK.
Panels A-D display the 10-week moving average time series of the RSJ, RVOL, RSK and RKT realized measures within RSK terciles.



A-2. Predictive Single Sorts for Alternative Estimators, Samples, and Returns

The main empirical results discussed in the paper are based on weekly realized variation measures spanning Tuesday-close to Tuesday-close constructed from five-minute transaction prices for all of the NYSE, NASDAQ and AMEX listed stocks. To assess the robustness of our results to these specific choices, this section reports the results in which we construct the realized measures based on mid-quotes, alternative subsampling procedures, restrict the sample to NYSE listed stocks only, rely on Monday-close to Monday-close or Wednesday-close to Wednesday-close realized measures and returns, as well as longer four-week prediction horizons. We begin by examining the sensitivity to the use of quote prices instead of transaction prices.

The bid-ask bounce effect in transaction prices tends to inflate the standard realized variation measure as well as the up and down semi-variance measures used in the calculation of the relative signed jump variation. Following common practice in the literature, our choice of a "coarse" 5-minute sampling frequency was explicitly intended to help mitigate these biases. To help further assess and reduce the impact of the bid-ask bounce effect, Panel A of Table A.1 reports the results for single-sorted portfolios in which the RSJ measures are calculated based on mid-quote returns instead of transaction price returns. The FFC4-adjusted High-Low spread for these alternative sorts equals -31.54 bps, with a t-statistic of -5.76, for the value-weighted portfolios, and -39.90 bps, with a t-statistic of -10.24, for the equal-weighted portfolios. Both the magnitude and the statistical significance of these abnormal returns are very similar to those reported in Panel A of Table 3 in the paper based on high-frequency transaction price returns.

A number of alternative realized variation estimators have also been proposed in the literature to help guard against the adverse effect of market microstructure "noise," including the bid-ask bounce effect. The subsampling methodology originally proposed by Zhang, Mykland, and Ait-Sahalia (2005), in particular, is designed to improve on the efficiency of sparsely-sampled realized volatility measures by averaging the estimators obtained across different sampling schemes. Our implementation of this alternative estimator relies on six different grids of 30-minute returns (starting from 9:30 a.m., 9:35 a.m., 9:40 a.m., 9:45 a.m., 9:50 a.m. and 9:55 a.m., respectively) from which we calculate six different daily relative signed jump variation estimators. We then average these six different daily estimators to obtain a single subsampled daily RSJ, which we use to compute a weekly subsampled RSJ as in equation (10). Panel B of Table A.1 reports the results from the single sorts based on this weekly subsampled RSJ estimator. Interestingly, the predictability becomes even stronger. The FFC4-adjusted High-Low spreads now equals -40.66 bps, with a t-statistic of -7.18, for the value-weighted portfolios, and -47.04 bps, with a t-statistic of -10.90, for the equal-weighted portfolios, all of which exceed (in an absolute value sense) the corresponding values based on the simple RSJ estimator reported in Panel A of Table 3 in the paper.

Our previous results were based on all of the stocks listed on the NYSE, NASDAQ, and AMEX exchanges. The results reported in Panel C in Table A.1 show that our findings of a negative relation between the relative signed jumps and the future returns remain intact in a sample consisting solely of NYSE listed stocks. In particular, even though the difference in the average abnormal returns between the High and Low RSJ-sorted portfolios based exclusively on the NYSE listed stocks equal to -25.27 bps, with a t-statistic of -5.21, for the value-weighted portfolios, and -13.60 bps, with a t-statistic of -3.93, for the equal-weighted portfolios, are slightly weaker, the results are still very much in line with those obtained for the larger sample comprised of all the stocks. As a general rule, the NYSE listed firms tend be larger and more liquid, thus again underscoring that our results aren't merely driven by market frictions and issues having to do with lack of liquidity.

Our empirical analysis so far has been based on weekly realized variation measures and subsequent weekly returns calculated from Tuesday-close to Tuesday-close. Alternatively, we estimate the weekly RSJ measures using the intraday returns between Monday-close and Monday-close, and between Wednesday-close and Wednesday-close, and then forecast the subsequent one-week-ahead returns. Panels D and E of Table A.1 present the results based on these two alternative weekly portfolio formation and return holding periods. For the Monday-close to Monday-close sorts, the FFC4-adjusted High-Low spread equals -36.22 bps, with a t-statistic of -7.13, for the value-weighted portfolios, and -44.12 bps, with a t-statistic of -10.98 for the equal-weighted portfolios. Both the spread and the t-statistic thus demonstrate a slightly stronger predictability of RSJ than the previously reported Tuesday-close to Tuesday-close results in Panel A of Table 3 in the paper. On the other hand, for the Wednesday-close to Wednesday-close sorts reported in Panel E, the predictability of RSJ is slightly weaker, albeit still highly statistically and economically significant.

The final set of results reported in Panel F of Table A.1 expand the weekly return horizon to a longer four-week holding period. For each portfolio formation week, we form quintile portfolios based on that week's RSJ measures, and then compute the value- and equal-weighted cumulative returns over the subsequent four weeks.[1] The average risk adjusted return spread between the resulting High and Low quintile portfolios equals -23.85 bps, with a t-statistic of -2.26, for the value-weighted portfolios. For the equal-weighted portfolios, the spread is -49.90 bps with a t-statistic of -5.37. Thus, even though the weekly RSJ-based portfolio formation continues to generate abnormal returns over this longer four-week return horizon, the results are obviously not as strong as the results for predicting the one-week-ahead returns.[2] The fact that the return predictability diminishes with the return horizon directly illustrates that the information in the firm specific RSJ measures is relatively short-lived, and as such indirectly suggests that the information isn't necessarily related to any underlying systematic risk factors.

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[1]By construction, this results in a three-week overlap between any two consecutive four-week returns, and return spreads. We rely on the Newey-West robust standard errors to adjust for this.

[2]The one-month-ahead return spreads based on the realized skewness measure RSK reported in ACJV are also not as significant as the one-week-ahead return spreads.

Table A.1: Predictive Single Sorts Based on Alternative Estimators, Samples, and Returns

This table reports the average returns for predictive single-sorted portfolios based on RSJ. At the end of each week, stocks are sorted into quintiles according to RSJ computed from the previous week's high-frequency returns. In Panel A, we use the high-frequency mid-quote prices to estimate weekly RSJ. In Panel B, we use RSJ estimated by subsampling methodology. In Panel C, we only consider stocks listed on NYSE. In Panel D/E, we compute RSJ estimates based on intraday data between Monday/Wednesday close and Monday/Wednesday close period and then forecast the subsequent weekly returns. In Panel F, we forecast the four-week ahead cumulative returns. The column labeled "Return" reports the average one-week or four-week ahead excess returns of each portfolio. The column labeled "FFC4" reports the corresponding Fama-French-Carhart four-factor alpha for each portfolio. The row labeled "High-Low" reports the difference in returns between portfolio 5 and portfolio 1, with Newey-West robust t-statistics in parentheses. In each panel, the first two columns report the value-weighted sorting results and the last two columns report the equal-weighted sorting results.

Panel A: RSJ Estimated by Mid-Quote Returns

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	34.91	18.24	57.67	38.07
2	25.92	10.06	34.31	14.98
3	14.49	-0.98	26.90	7.70
4	6.35	-9.21	21.56	2.58
5(High)	2.48	-13.30	17.00	-1.83
High-Low	-32.43	-31.54	-40.68	-39.90
	(-5.88)	(-5.76)	(-9.83)	(-10.24)

Panel B: RSJ Estimated by Subsampling

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	38.05	21.87	61.17	41.66
2	23.61	7.71	38.02	18.57
3	14.66	-1.08	25.60	6.12
4	9.91	-5.53	20.94	2.08
5(High)	-2.98	-18.79	12.88	-5.39
High-Low	-41.03	-40.66	-48.28	-47.04
	(-7.28)	(-7.18)	(-10.55)	(-10.90)

Panel C: NYSE Sample

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	28.91	12.73	34.85	14.67
2	22.74	6.31	29.05	9.21
3	13.44	-2.43	25.99	6.22
4	8.27	-7.72	20.96	1.42
5(High)	3.30	-12.54	20.17	1.07
High-Low	-25.61	-25.27	-14.69	-13.60
	(-5.33)	(-5.21)	(-4.22)	(-3.92)

Panel D: Monday-Close to Monday-Close

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	37.62	20.79	58.04	38.73
2	24.37	7.58	41.40	21.30
3	20.45	4.30	29.63	9.61
4	8.38	-7.78	21.24	1.36
5(High)	0.29	-15.42	13.50	-5.39
High-Low	-37.34	-36.22	-44.54	-44.12
	(-7.10)	(-7.13)	(-10.35)	(-10.98)

Panel E: Wednesday-Close to Wednesday-Close

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	32.60	16.32	50.55	31.57
2	22.64	6.89	37.21	18.02
3	19.46	4.13	30.76	11.58
4	9.75	-5.58	21.30	2.36
5(High)	4.83	-10.94	18.40	-0.44
High-Low	-27.76	-27.26	-32.15	-32.01
	(-5.71)	(-5.52)	(-8.59)	(-8.64)

Panel F: Four-Week Holding Period Return

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	77.63	15.05	139.9	71.57
2	74.47	13.67	118.16	48.98
3	57.87	-0.09	106.8	37.97
4	51.36	-6.83	93.21	23.86
5(High)	46.67	-8.8	90.62	21.67
High-Low	-30.96	-23.85	-49.28	-49.9
	(-2.98)	(-2.26)	(-5.19)	(-5.37)

A-3. Double-sorted portfolios with additional controls

To further investigate the robustness of our findings, we document the results from a series of additional double sorts based on the same sequential sorting approach employed in Section V, using other control variables. To conserve space, we do not report the average returns for all the 25 portfolios for each of the different sorts, focussing instead on the returns for the quintile portfolios averaged across the first sorting variable to produce portfolios with large variation in the second sorting variable, but small variation in the control.

Panel A of Table A.2 reports the results in which the final sorts are based on RSJ. The strong predictability of RSJ is preserved across all of the different control variables. The value-weighted average weekly return spread between the High and Low quintile portfolios ranges from -15.32 bps, with a t-statistic of -3.83, after controlling for REV, to -40.07 bps, with a t-statistic of -8.09, after controlling for RVOL. The spreads in the FFC4 alphas are almost always very close to those for the raw returns, both in terms of their absolute magnitudes and the t-statistics. The equal-weighted average weekly return spread ranges from -17.32 bps, with a t-statistic of -6.29, after controlling for REV, to -39.67 bps, with a t-statistic of -9.96, after controlling for IVOL. The Fama-French-Carhart four factors again provide little explanation for these return spreads between the equal-weighted High and Low RSJ-sorted portfolios. The past week's return and the realized skewness offer the highest explanatory power for the RSJ effect, as manifested by the smallest value-weighted FFC4 spreads of -21.39 bps in the RSK column and -14.35 bps in the REV column.

However, both of these spreads remain highly statistically significant and economically large, further corroborating the idea that RSJ contains unique predictive information.

Panel B shows the results for the corresponding sequential portfolio sorts, in which the final sorts are based on RSK. Consistent with the evidence in ACJV, the negative relation between RSK and future returns generally remains intact across the various control variables. At the same time, however, the abnormal returns and the associated t-statistics are generally smaller than their counterparts based on the RSJ double sorts reported in Panel A. Importantly, as discussed in the main text, the double sorts that control for RSJ completely changes the sign, and reveals a statistically significant *positive* relation between the realized skewness and the future returns. Also, after controlling for REV, the value-weighted return spread for the High-Low RSK-sorted portfolios and the corresponding FFC4 alpha are no longer significant. By contrast, RSJ-based sequential sorts always result in the same highly statistically significant negative return predictability across *all* of the controls.

Table A.2: Predictive Double-Sorted Portfolios with Additional Controls

The table reports the average returns for predictive double-sorted portfolios. The sample consists of all the NYSE, AMEX and NASDAQ listed common stocks with share codes 10 or 11 and prices between $5 and $1,000 over the 1993-2013 sample period. For each week, all stocks in the sample are first sorted into five quintiles on the basis of one control variable. Within each quintile, the stocks are then sorted into five quintiles according to their RSJ/RSK. These five RSJ/RSK portfolios are then averaged across the five control variable portfolios to produce RSJ/RSK portfolios with large cross-portfolio variation in their RSJ/RSK but little variation in the control variable. RSJ, RVOL, RSK, and RKT denote the relative signed jump, realized volatility, realized skewness, and realized kurtosis, respectively. Beta denotes the standard CAPM beta. ME denotes the logarithm of the market capitalization of the firms. BM denotes the ratio of the book value of common equity to the market value of equity. MOM is the compound gross return from day $t-252$ through day $t-21$. REV is the lagged one-week return. IVOL is a measure of idiosyncratic volatility. CSK and CKT are the measures of coskewness and cokurtosis, respectively. MAX and MIN represent the maximum and minimum daily raw returns over the previous week. ILLIQ refers to the logarithm of the average daily ratio of the absolute stock return to the dollar trading volume over the previous week. The first five rows in both value-weighted and equal-weighted sorting results report time-series averages of weekly excess returns for the RSJ/RSK quintile portfolios. The row labeled "High-Low" reports the difference in the returns between portfolio 5 and portfolio 1. The row labeled "FFC4" reports the average Fama-French-Carhart four-factor alphas. The corresponding Newey-West robust t-statistics are reported in parentheses. Panels A and B display the results for the portfolios first sorted by the control variables listed in the columns and then by RSJ or RSK, respectively.

Panel A: Final Sorted by RSJ

Quintile	RVOL	RSK	RKT	Beta	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
							Value-Weighted							
1(Low)	42.96	30.53	34.14	35.34	47.63	33.01	33.50	25.00	35.63	33.11	32.75	32.71	32.61	42.15
2	27.88	20.37	21.67	23.19	38.50	22.49	25.00	20.00	25.00	23.70	21.55	22.61	23.97	28.95
3	21.96	16.81	14.83	15.92	28.24	16.68	15.98	16.28	15.36	13.56	15.16	14.66	14.67	21.17
4	9.32	12.33	12.32	10.72	19.72	11.94	9.49	15.40	8.55	9.13	9.67	12.42	13.92	15.17
5(High)	2.89	8.15	7.06	2.68	14.41	6.10	3.36	9.68	-1.28	3.10	4.09	2.66	7.78	9.34
High-Low	-40.07	-22.38	-27.08	-32.66	-33.22	-26.91	-30.14	-15.32	-36.91	-30.01	-28.66	-30.04	-24.83	-32.81
	(-8.09)	(-5.43)	(-6.07)	(-8.05)	(-8.63)	(-6.04)	(-6.62)	(-3.83)	(-7.47)	(-6.30)	(-6.16)	(-5.76)	(-6.17)	(-8.09)
FFC4	-40.03	-21.39	-26.38	-32.58	-32.58	-26.11	-29.66	-14.35	-36.74	-29.25	-27.77	-28.64	-25.04	-32.21
	(-8.19)	(-5.16)	(-5.98)	(-8.14)	(-8.77)	(-5.89)	(-6.73)	(-3.60)	(-7.57)	(-6.28)	(-5.98)	(-6.18)	(-6.06)	(-8.16)
							Equal-Weighted							
1(Low)	53.90	45.74	54.47	53.73	50.25	51.71	54.00	40.41	47.07	46.74	46.38	52.47	47.72	56.34
2	39.59	38.27	38.71	36.53	39.87	37.41	37.82	35.31	32.86	31.61	31.61	37.58	38.05	38.33
3	31.48	31.27	31.00	30.95	30.98	30.02	30.87	30.76	25.72	24.08	24.29	29.78	31.07	30.40
4	22.85	28.47	23.75	21.21	22.55	20.86	20.59	27.40	17.11	17.72	18.14	22.31	26.59	22.28
5(High)	16.67	20.46	16.43	15.59	16.88	16.62	16.38	23.10	7.40	9.84	9.57	18.63	17.05	16.87
High-Low	-37.23	-25.28	-38.03	-38.14	-33.36	-35.10	-37.62	-17.32	-39.67	-36.90	-36.81	-33.84	-30.67	-39.47
	(-10.89)	(-7.40)	(-8.79)	(-11.03)	(-8.60)	(-9.39)	(-10.59)	(-6.29)	(-9.96)	(-7.85)	(-8.02)	(-7.61)	(-10.26)	(-8.67)
FFC4	-36.68	-24.22	-37.25	-37.60	-32.74	-34.22	-36.95	-17.02	-38.92	-36.13	-36.01	-32.14	-31.08	-39.00
	(-11.07)	(-7.38)	(-9.09)	(-11.19)	(-8.78)	(-9.39)	(-11.12)	(-6.28)	(-10.02)	(-8.04)	(-8.16)	(-8.71)	(-10.31)	(-8.88)

Panel B: Final Sorted by RSK

Quintile	RSJ	RVOL	RKT	Beta	ME	BM	MOM	REV	IVOL	CSK	CKT	MAX	MIN	ILLIQ
							Value-Weighted							
1(Low)	13.07	35.08	28.62	28.83	43.20	27.11	26.82	21.15	29.71	28.68	27.61	26.93	28.45	37.26
2	15.05	31.77	20.86	21.19	37.60	22.45	24.76	18.22	25.85	21.79	23.79	21.34	21.80	29.62
3	14.57	18.18	16.73	17.07	28.11	17.38	16.62	18.14	14.45	16.45	13.42	16.50	17.25	20.41
4	20.90	13.73	15.42	11.89	22.71	12.73	11.48	14.74	11.43	10.23	11.03	11.12	15.49	16.97
5(High)	24.91	7.67	9.00	6.18	16.75	10.12	6.94	16.49	4.04	5.53	7.91	8.98	11.42	12.10
High-Low	11.84	-27.41	-19.62	-22.65	-26.46	-16.99	-19.88	-4.66	-25.67	-23.15	-19.69	-17.95	-17.03	-25.16
	(3.50)	(-6.94)	(-5.19)	(-6.64)	(-8.77)	(-4.45)	(-5.50)	(-1.32)	(-6.41)	(-5.86)	(-5.20)	(-4.35)	(-4.86)	(-7.72)
FFC4	11.73	-26.67	-18.45	-22.66	-26.01	-16.05	-19.20	-3.70	-24.80	-22.50	-18.67	-16.39	-16.89	-24.43
	(3.45)	(-6.74)	(-4.91)	(-6.65)	(-8.89)	(-4.17)	(-5.45)	(-1.04)	(-6.23)	(-5.69)	(-4.89)	(-4.25)	(-4.72)	(-7.68)
							Equal-Weighted							
1(Low)	30.08	48.96	49.99	49.34	46.23	47.69	49.31	38.61	42.48	43.02	42.13	47.44	44.61	51.71
2	32.06	39.50	38.84	36.31	39.12	37.26	37.02	34.16	32.29	30.65	31.72	36.90	37.44	38.60
3	31.58	30.93	30.14	29.51	30.76	28.92	29.56	31.16	23.44	22.95	22.28	30.18	30.61	29.24
4	33.77	25.52	27.10	24.11	25.37	23.55	24.07	26.42	20.48	20.55	19.52	24.29	27.00	25.35
5(High)	37.15	19.60	18.41	18.70	19.13	19.34	19.65	26.58	11.81	13.40	14.31	21.78	20.82	19.36
High-Low	7.07	-29.36	-31.57	-30.63	-27.10	-28.35	-29.66	-12.03	-30.66	-29.62	-27.82	-25.66	-23.79	-32.35
	(2.93)	(-10.95)	(-8.72)	(-11.07)	(-8.96)	(-9.53)	(-10.27)	(-5.16)	(-9.80)	(-7.87)	(-7.72)	(-7.40)	(-9.58)	(-8.90)
FFC4	6.27	-29.11	-31.11	-30.38	-26.87	-28.08	-29.46	-11.81	-30.34	-29.35	-27.52	-24.55	-24.25	-32.15
	(2.63)	(-11.10)	(-9.02)	(-11.17)	(-9.20)	(-9.62)	(-10.74)	(-5.09)	(-9.88)	(-8.07)	(-7.89)	(-8.30)	(-9.76)	(-9.16)

A-4. Relative Signed Jumps and Other Firm Characteristics

This section reports the results from additional cross-sectional regressions designed to investigate the relationship between the relative signed jump variation measure RSJ and other firm characteristics. Motivated by previous empirical findings related to the cross-sectional variation in standard measures of return skewness (e.g., Hong, Wang, and Yu (2008) and Engle and Mistry (2014)), we focus on size (ME), book-to-market ratio (BM), leverage (LEVERAGE), and credit rating (CREDIT). ME and BM are computed as discussed in the main text. LEVERAGE refers to the ratio of book value of debt over market value of equity.[3] CREDIT refers to the Standard and Poor's credit rating available monthly from Compustat.[4]

Turning to the results, the coefficient associated with market size ME in Regression I is small and insignificant. In Regression II the coefficient of BM equals 0.0044, with a t-statistic of 5.57. The average cross-sectional standard deviations of BM and RSJ in our sample are 0.63 and 0.16, respectively. A two-standard deviation increase in BM thus leads to an increase in RSJ of $2 \times 0.63 \times 0.0044$, or about 3.5% of the standard deviation of RSJ. In Regression III the coefficient for LEVERAGE equals -0.0002, with a t-statistic of -2.04,

[3]The book value of debt is the total asset, minus the book value of common equity, minus deferred taxes and investment tax credit.

[4]Following Amaya, Christoffersen, Jacobs, and Vasquez (2016), we assign numerical grades to the ratings: 1-AAA, 2-AA+, 3-AA, 4-AA-,5-A+, until 22-D.

again suggesting that a firm's leverage is negatively related to it's relative signed jump variation. However, the economic effect is small. A two-standard deviation increase in LEVERAGE is associated with a decrease in the firm RSJ of only $2 \times 3.72 \times 0.0002$, or around 1% of the standard deviation of RSJ. Lastly, the t-statistic of -1.13 in Regression IV indicates that CREDIT is not significantly related to RSJ. All-in-all, no strong empirical relationship between RSJ and the other explanatory variables emerges from these regressions.

Table A.3: Fama-MacBeth Cross-Sectional Regressions for RSJ

The table displays the average estimated regression coefficients and robust t-statistics (in parentheses) from Fama-MacBeth cross-sectional regressions for the weekly RSJs. The sample consists of all the NYSE, AMEX and NASDAQ listed common stocks with share codes 10 or 11 and prices between $5 and $1,000 over the 1993-2013 sample period. ME refers to the logarithm of the market capitalization of the firms. BM denotes the ratio of the book value of common equity to the market value of equity. LEVERAGE denotes book debt divided by market equity. CREDIT is assigned a numerical value as follows: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21 and D=22.

Regression	ME	BM	LEVERAGE	CREDIT
I	-0.0002			
	(-0.70)			
II		0.0044		
		(5.57)		
III			-0.0002	
			(-2.04)	
IV				-0.0001
				(-1.13)
V	-0.0005	0.0061	-0.0005	-0.0004
	(-1.43)	(7.43)	(-4.27)	(-2.67)

A-5. Frequency Analysis of RSJ and RSK

The actual sample values of the different realized measures invariably depend on the sampling frequency of the returns used in their estimation. Along these lines, RSJ generally affords more robust measurements than RSK. The table below, in particular, presents the correlations between weekly RSJs and RSKs computed with returns sampled at different frequencies. As the table shows, the correlations between the differently estimated weekly RSJ measures are in general higher than the correlations among the weekly RSK measures.

Panel A: Weekly RSJ Correlation

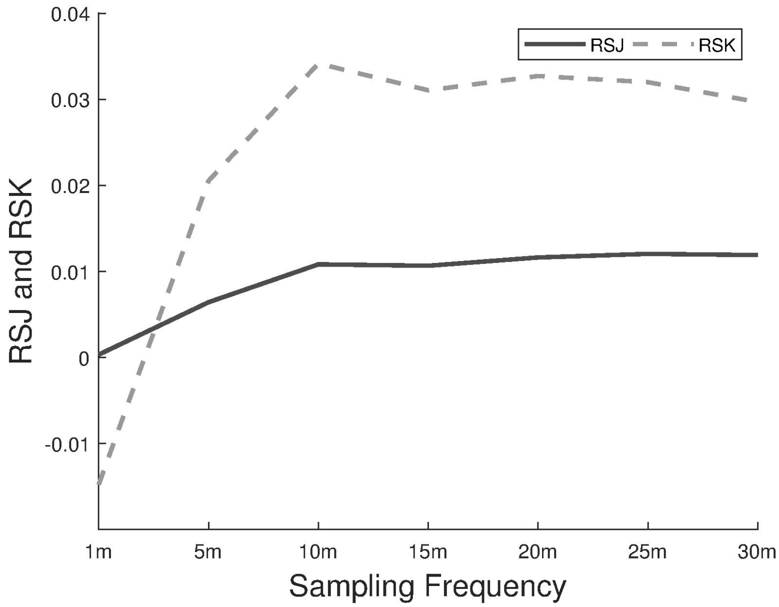
	1-min	5-min	10-min	15-min	20-min	25-min	30-min
1-min	1	0.88**	0.82**	0.79**	0.78**	0.76**	0.75**
5-min		1	0.93**	0.90**	0.88**	0.86**	0.85**
10-min			1	0.93**	0.93**	0.90**	0.89**
15-min				1	0.93**	0.93**	0.93**
20-min					1	0.93**	0.93**
25-min						1	0.93**
30-min							1

Panel B: Weekly RSK Correlation

	1-min	5-min	10-min	15-min	20-min	25-min	30-min
1-min	1	0.78**	0.68**	0.63**	0.61**	0.58**	0.56**
5-min		1	0.88**	0.81**	0.78**	0.75**	0.72**
10-min			1	0.87**	0.88**	0.82**	0.80**
15-min				1	0.87**	0.87**	0.86**
20-min					1	0.86**	0.86**
25-min						1	0.86**
30-min							1

The signature plots below, depicting the time-series averages of the cross-sectional means of RSJ and RSK for sampling frequencies ranging from 1-minute to 30-minutes, further underscore this same robustness of RSJ vis-a-vis RSK.

Fig. A.4: Signature Plots of RSJ and RSK.
This figure shows the signature plots of weekly RSJ and RSK computed from different return frequencies ranging from 1 minute to 30 minutes.



As discussed in the main text, the RSJ measure also provides a much "cleaner" and easier to interpret asymptotic limit (for increasingly higher sampling frequencies). By contrast, the expected value of RSK depends on the sampling frequency used in the estimation. Koike and Liu (2018), "Asymptotic properties of the realized skewness and related statistics," *Annals of the Institute of Statistical Mathematics*, provides a recent attempt at establishing a more complicated limit theory (for increasingly higher sampling frequencies) for the RSK measure.

A-6. Relative Signed Return

It is possible that the superiority of RSJ compared to RSK stem from the fact that RSJ only uses second powers of high-frequency returns, while RSK rely on third powers. If so, the use of absolute returns instead of squared returns in the definition of positive and negative semi-variances in equation (4) could possibly result in even stronger predictability results.[5]

To investigate this conjecture, we replace the squared returns in the calculation of the RSJ measure with the corresponding absolute returns, referring to this alternative measure as relative signed return (RSR). Not surprisingly, RSR does indeed predict future returns, as is evident by the single-sorts in the table below.

Single Sort by RSR

	Value-Weighted		Equal-Weighted	
Quintile	Return	FFC4	Return	FFC4
1(Low)	37.15	20.83	58.22	38.82
2	23.55	7.81	39.54	20.21
3	15.26	-0.59	26.27	6.88
4	9.22	-6.39	20.99	2.03
5(High)	-2.11	-17.97	13.60	-4.90
High-Low	-39.26	-38.80	-44.62	-43.72
	(-6.73)	(-6.69)	(-9.61)	(-9.97)

These predictability results for RSR also closely mirror the RSJ-based single-sorts reported in Table 3 in the paper. Furthermore, in Fama-MacBeth regressions that simultaneously control for RSJ, RSK and RSR, both RSJ and RSR significantly (and negatively) predict the one-week-ahead returns, while the effect of RSK is again reversed.

[5]We thank the referee for this suggestion.

Meanwhile, the asymptotic limit (for increasingly higher sampling frequencies) of RSJ is much "cleaner" and easier to understand than the limit for RSR. In particular, as discussed in the main text, in the absence of jumps, RSJ should be identically equal to zero (again, under the usual in-fill asymptotic arguments). By contrast, the unscaled sum of the absolute high-frequency returns formally diverges for increasingly finer sampled returns (the sum needs to be scaled by $\Delta^{1/2}$, where $\Delta = 1/M$ denotes the length of the high-frequency return interval). However, if we scale the sum of the absolute returns by $\Delta^{1/2}$ in order to obtain a well-defined limit, that same scaling then "kills" the jumps. Formally, for the jump-diffusion process,

$$dp(t) = \mu(t) + \sigma(t)dW(t) + \kappa(t)dq(t),$$

it follows that for $M \to \infty$ (see, e.g., Barndorff-Nielsen and Shephard (2004), "Power and bipower variation with stochastic volatility and jumps," *Journal of Financial Econometrics*),

$$\mathrm{RV}_t \xrightarrow{M\to\infty} \mathrm{IV}_t + \Sigma_{s\in[0,t]:dq(s)=1}\kappa^2(s),$$

$$\mathrm{RAV}_t \equiv \mu_1^{-1}M^{-1/2}\Sigma_{i=1}^{M}|r_{t,i}| \xrightarrow{M\to\infty} \int_0^t \sigma(s)ds,$$

with the obvious extensions to the signed semi-versions of the measures. Hence, in the limit RSJ and RSR formally measure different things. In practice, of course, with a fixed Δ (or fixed M) that is somewhat mute. This also explains why the two measures provide very complimentary empirical evidence. However, in lieu of the "cleaner" asymptotic theory and interpretation associated with RSJ we prefer that measure.