Good Jumps, Bad Jumps, and Conditional Equity Premium*

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We uncover significant effects of jump risk on conditional equity premium. Realized volatility due to negative or "bad" (positive or "good") jumps in stock market prices predicts a rising (falling) near-term equity premium. The forecasting power of signed jump risk measures remains statistically significant even when we control for variance risk premium that Drechsler and Yaron (2011) attribute to jump risk. Our novel empirical findings are broadly consistent with an extended Drechsler and Yaron model that also allows stochastic volatility of volatility to affect variance risk premium and conditional equity premium as in Bollerslev, Tauchen, and Zhou (2009).

JEL classification: G10, G12, G17.
Keywords: Realized Jump Risk, Good and Bad Jumps, Conditional Equity Premium, Downside Economic Uncertainty, Variance Risk Premium.

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1 Introduction

This paper documents a novel and important empirical finding that physical jump risk measures are a significant determinant of conditional equity premium even when we control for commonly used stock market return predictors. To do this, we decompose realized stock market return volatility into (1) a continuous diffusion risk part and (2) a discrete jump risk part, and then decompose the latter, i.e., the total realized jump volatility, into (1) a component for negative or "bad" jumps and (2) a component for positive or "good" jumps. Over the January 1986 to December 2013 period, the two jump risk components affect conditional equity premium with *opposite* signs and different significance. Specifically, the volatility of negative jumps correlates positively and significantly with one-month-ahead excess stock market returns, while the correlation is negative albeit insignificant for the volatility of positive jumps. The difference between bad and good jump risks is also a parsimonious signed jump risk measure that correlates positively and significantly with future equity premium. By contrast, the predictive power is negligible for the total realized jump volatility that allows for no asymmetric effects.

Our main empirical findings pass easily standard robustness checks for stock market return predictability. First, despite drastic changes in market conditions over a relatively short sample period, the signed jump risk measure has significant predictive power for excess market returns in two half samples. Second, the signed jump risk measure outperforms the benchmark model of constant conditional equity premium in the out of sample test, and the difference is statistically significant at the 5% level. Last, we construct a simple switching trading strategy of holding the market portfolio when the signed jump risk measure predicts a positive equity premium and holding the risk-free T-bill otherwise. The Sharpe ratio of our switching strategy is about 20% higher than that of a buy-and-hold strategy.

Drechsler and Yaron (2011) (DY thereafter) analyze effects of jump risk on asset prices, and we show via simulation that their model provides a potential explanation for the observed (asymmetric) effects of jump risk on conditional equity premium. Because jump intensity is a linear function of conditional volatility, realized jump volatility correlates positively with conditional volatility. In addition, conditional equity premium is proportional to conditional volatility. Hence, in the DY model, realized jump risk forecasts equity premium because of its correlation with conditional volatility. Moreover, the correlation with conditional volatility is much stronger for negative jumps than for positive jumps due to the assumed jump size distributions. Therefore, the DY model may account for our two main findings: (1) Negative jump risk has significant effects on conditional equity premium but positive jump risk does not; and (2) the signed jump risk measure forecasts excess market returns.

In the DY model, jumps generate a positive variance risk premium (the difference between options-implied stock variance and realized stock variance) which, like the signed jump risk measure, predicts excess market returns because of its correlation with conditional volatility. The DY model thus implies that variance risk premium and the signed jump risk measure contain similar information about future equity premium. We confirm this point by showing that in simulated data, the former often drives out the latter in the regression of forecasting excess market returns. By contrast, in actual data, both variance risk premium and the signed jump risk measure are significant predictors of equity premium in bivariate regressions. The empirical finding indicates that jump risk is not the sole driver of variance risk premium: Variance risk premium affects conditional equity premium through additional channels that are independent of jump risk. To address this issue formally, we propose an extended DY model allowing for stochastic volatility of volatility as an additional determinant of both variance risk premium and conditional equity premium as in Bollerslev, Tauchen, and Zhou (2009). Under reasonable parameterizations, the extended DY model implies that consistent with our empirical evidence, variance risk premium and the signed jump risk measure contain independent information about future equity premium.

There is an ongoing debate about whether excess stock market returns or equity premia are predictable over time. Specifically, Goyal and Welch (2008) caution about data mining and show using a long sample that the predictive variables proposed in the extant literature have rather weak forecasting power for excess stock market returns, especially in the out-of-sample context. To address this concern, recent studies investigate stock market return predictability using theoretically motivated risk measures such as stock market variance (Guo and Whitelaw (2006)) and variance risk premium (Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011)). We contribute to this literature by showing empirically and theoretically that jump risk is also an important determinant of conditional equity premium. Our novel findings shed new light on economic drivers of time-varying equity premium.

Many authors, e.g., Rietz (1988), Longstaff and Piazzesi (2004), Liu, Pan, and Wang (2005), Barro (2006), Bates (2008), Eraker and Shaliastovich (2008), Bansal and Shaliastovich (2011), Drechsler and Yaron (2011), Du (2011), Gabaix (2012), and Wachter (2013), incorporate rare disaster or jump risk in consumption-based asset pricing models. They show that investors require a substantial return premium for bearing the market-wide jump risk that may potentially resolve the Mehra and Prescott (1988) equity premium puzzle. Using options data and parametric models, extant empirical studies, e.g., Bates (1996), Bakshi, Cao, and Chen (1997), Pan (2002), Eraker (2004), Broadie, Chernov, and Johannes (2007), and Santa-Clara and Yan (2010), find that jump risk accounts for a sizable portion of the unconditional equity premium. We extend this literature by testing a more direct and stringent implication that the *physical* measure of market-wide jump risk is an important determinant of *conditional* equity premium.[1] Indeed, we find that realized jump risk—especially negative or bad jumps—correlates positively with future excess stock market returns. This novel evidence offer new insight on how jump risk affects asset prices.

Kelly and Jiang (2014) report a positive relation between downside tail risk constructed from daily cross-sectional stock returns and conditional equity premium. Bollerslev and Todorov (2011) document time-series variation in jump-related equity premium estimated using options data. Du and Kapadia (2012) uncover a positive relation between a risk-neutral jump risk measure and future stock market returns by focusing on left tails. Similarly, there is strong indication that jump risk premium implied by options, especially the negative component, explains well future market returns (Bollerslev, Todorov, and Xu, 2014).[2] Our econometric identification of realized jumps follows Huang and Tauchen (2005) and Tauchen

[1]Options-implied or risk-neutral jump risk measure is potentially a biased proxy for physical jump risk measure because it contains a risk premium component.

[2]Bali and Hovakimian (2009), Yan (2011), Cremers, Halling, and Weinbaum (2011), and Jiang and Yao (2013) find that jump risk estimated from option data forecasts the cross-section of stock returns.

and Zhou (2011), and the method of decomposing jump risk into good and bad components follows Zhang, Zhou, and Zhu (2009). Previous studies show that realized jump risk predicts excess bond returns (Wright and Zhou, 2009) and credit spreads (Tauchen and Zhou, 2011). Yet, there is no compelling evidence that realized jump risk predicts excess stock returns unless, as we stress in this paper, it is decomposed into bad and good jump risks.[3]

Recent empirical evidence suggests that good and bad economic uncertainties or volatilities have different forecasting power for asset prices and macroeconomic performance (Segal, Shaliastovich, and Yaron, 2014). Likewise, good and bad market volatilities pertain distinct information about future stock market returns (Feunou, Jahan-Parvar, and Tedongap, 2012); and negative (positive) market jump risks lead to significantly higher (lower) future market volatilities (Patton and Sheppard, 2013). We add to this literature by documenting novel asymmetric effects of physical jump risk measures on conditional equity premium and future economic fundamentals. Interestingly, Kilic and Shaliastovich (2015) report asymmetric effects of good and bad variance premium on expected excess market returns using a signing method similar to ours.

The remainder of the paper is organized as follows. Section 2 explains the realized jump risk measure and its decomposition into good and bad components. Section 3 investigates the relationship between realized jump risk and future excess market returns. Section 4 explains our main empirical findings using the DY and extended DY models. Section 5 concludes.

2 Econometric Estimation of Realized Jump Risk

We construct realized jump risk measures using high-frequency data. Andersen, Bollerslev, Diebold, and Ebens (2001), Barndorff-Nielsen and Shephard (2002), and others, advocate for using the sum of squared intra-day returns to estimate realized variance (RV). Barndorff-Nielsen and Shephard (2004, 2006) (BNS thereafter) develop the bipower variation (BV) to estimate the continuous variation, and show that asymptotically the difference between RV and BV equals zero when there is no jump and is strictly positive when there is a jump. We

[3] Dungey, Mckenzie, and Smith (2009), Becker, Clement, and McClelland (2009), Jiang, Lo, and Verdelhan (2011), and Lahaye, Laurent, and Neely (2011) have investigated realized jump risk in other financial markets.

use this test to detect whether a jump occurs on a trading day and then construct realized jump risk measures accordingly. Below we provide a brief discussion of our econometric approach, which is similar to the one adopted by Tauchen and Zhou (2011).

We assume that the log of stock price $s_t = \log(S_t)$ follows a general jump diffusion model:

$$ds_t = \mu_t dt + \sigma_t dW_t + J_t dq_t, \tag{1}$$

where μ_t is a drift, σ_t is diffusion volatility, W_t is a standard Brownian motion, dq_t is a Poisson jump process, and J_t is the jump size that follows a normal distribution with the mean μ_J and the standard deviation σ_J. The i-th intra-day return of day t is $r_{t,i} = s_{t,i\cdot\tau} - s_{t,(i-1)\cdot\tau}$, where τ is the sampling interval. The realized variance of day t is

$$RV_t \equiv \sum_{i=1}^{M} r_{t,i}^2, \tag{2}$$

where M is the number of intra-day observations. The bipower variation of day t is

$$BV_t \equiv \frac{\pi}{2}\frac{M}{M-1}\sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}|. \tag{3}$$

Similar to Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007), we choose the following jump test statistic

$$ZJ_t \equiv \frac{\frac{RV_t - BV_t}{RV_t}}{\sqrt{(\frac{\pi^2}{4}+\pi-5)\frac{1}{M}\max(1, \frac{TP_t}{BV_t^2})}}, \tag{4}$$

where TP_t is the tripower quarticity that Barndorff-Nielsen and Shephard (2004) define as

$$TP_t = \frac{M}{M-2}\cdot\frac{M}{4[\Gamma(7/6)/\Gamma(1/2)]^3}\cdot\sum_{i=3}^{M} |r_{t,i}|^{4/3}|r_{t,i-1}|^{4/3}|r_{t,i-2}|^{4/3}. \tag{5}$$

The test statistic has an asymptotic normal distribution under the null hypothesis of no jump. If the test statistic of day t exceeds the 0.1% critical value of normal distribution, we reject the null hypothesis. The dummy variable $I_{t,\alpha}$ equals 1 when a jump is detected at day t and 0 otherwise, i.e., $I_{t,\alpha} = I(ZJ_t \geq \Phi_\alpha^{-1})$, where Φ is the standard normal distribution and $\alpha = 99.9\%$ is the chosen significance level. Then the realized jump volatility (RJV) is

$$RJV_t = I_{t,\alpha}\sqrt{[RV_t - BV_t]}. \tag{6}$$

As we will show both empirically (Section 3) and theoretically (Section 4), positive and negative jumps have different effects on conditional equity premium. To investigate this issue, following Tauchen and Zhou (2011) and others, we use two assumptions to identify the sign of a jump. First, there is at most one jump in a trading day. Second, a jump has a dominant effect on the stock return for the day when it occurs. Under these two assumptions, the sign of a jump is the same as the sign of the stock return for the day when the jump occurs. Therefore, the risk due to a positive/good jump is

$$RJV\_P_t = I\{r_t \geq 0\} RJV_t; \tag{7}$$

and the risk due to a negative/bad jump is

$$RJV\_N_t = I\{r_t < 0\} RJV_t. \tag{8}$$

As we will show in the next section, RJV_N correlates positively with future stock market returns, while the correlation is negative for RJV_P. To incorporate such an asymmetric effect of jump risk on conditional equity premium, we construct a composite signed jump risk measure—the difference between RJV_N and RJV_P:

$$RJV\_SIGNED_t = RJV\_N_t - RJV\_P_t. \tag{9}$$

3 Realized Jump Risk and Expected Stock Returns

This section provides new empirical evidence that negative or signed jump risk significantly predicts a rising equity premium, although the forecasting power is negligible for the total jump risk. The predictability is the strongest at the short 1- to 2-month horizon, survives out-of-sample tests, produces significant market timing gains, and is robust with the control of standard forecasting variables, including the powerful short-term predictor—variance risk premium. In addition, consistent with a risk-based explanation, downside jump risk precedes deterioration in economic fundamentals and is priced in the cross-section of stock returns.

3.1 Data Summary

We detect daily jumps in the aggregate S&P 500 composite index using 5-minute high-frequency data (excluding after-hour trading), spanning the sample period from January 1986 to December 2013. Trading days with less than 60 observations of 5-minute returns are deleted from our sample. We construct daily realized jump risk measures and then aggregate them across a month to obtain monthly observations. The monthly value-weighed stock market return and risk-free rate are obtained from the Center for Research in Security Prices (CRSP). The excess stock market return, ERET, is the difference between the stock market return and the risk-free rate. We obtain commonly used stock market return predictors from Amit Goyal's website at the University of Lausanne. The monthly industrial output and effective federal funds rate data are from the website of Federal Reserve Bank of St. Louis.

The upper panel of Figure 1 shows that realized jump volatility (RJV) appears to change countercyclically over time. Specifically, RJV increases during business recessions (denoted by shaded areas) and financial market turmoils and is relatively flat during other periods. Figure 2 reveals a similar countercyclical pattern for it components—realized positive jump volatility (RJV_P, upper panel) and especially, realized negative jump volatility (RJV_N, lower panel). In Section 3.6, we will show formally that RJV_N correlates negatively and significantly with aggregate economic activity and the effective federal funds rate. Realized signed jump volatility (RJV_SIGNED)—the difference between RJV_N and RJV_P—varies visibly differently from RJV over time (lower panel, Figure 1). Specifically, it shoots up sharply just before or at the onset of the three business recessions in our sample. This difference may explain why RJV_SINGED has significant predictive power for both excess market returns and economic fundamentals while RJV does not.

In Table 1, we report summary statistics of the excess market return (ERET) and realized jump risk measures. Panel A presents univariate statistics. The sample mean of RJV_N is smaller than that of RJV_P, and their difference, RJV_SIGNED, thus has a negative sample mean. The autocorrelation coefficient for RJV_N (33%) is noticeably higher than that of RJV_P (15%), indicating that negative jumps are more persistent than positive jumps.

RJV also has moderate persistence, with an autocorrelation coefficient of 31%. In contrast, the intertemporal dependence is rather weak for RJV_SIGNED, with an autocorrelation coefficient of 5%. Panel B reports the cross-correlation. RJV_N correlates negatively with ERET, while the correlation is positive for RJV_P. As a result, RJV_SIGNED, which is the difference between RJV_N and RJV_P, correlates negatively with ERET. Results reported in panel B also suggest that on average negative jumps have a larger contemporaneous impact on the stock market price index than do positive jumps—the correlations of ERET with RJV_N and RJV_P are -13% and 1%, respectively. The correlation with ERET is negative for RJV, which is the sum of RJV_N and RJV_P, but the magnitude is moderate (-8%). Moreover, consistent with Figure 2 that RJV_N and RJV_P appear to move together to each other over business cycles, there is a positive correlation between these two variables (31%).

3.2 Signed Jump Volatility and Expected Stock Market Returns

Table 2 presents ordinary least squares (OLS) estimation results of forecasting one-month-ahead excess market returns using realized jump risk measures. Contrary to the conventional wisdom that jump risk has pervasive effects on asset prices (Merton, 1976), row 1 shows that the predictive power is negligible for the total realized jump volatility, RJV. However, when decomposing jump risk into positive and negative components, we are able to uncover its economically large and statistically significant effects on conditional equity premium.

Row 2 of Table 2 shows that RJV_N, the risk due to negative or bad jumps, correlates positively and significantly with future excess market returns at the 5% level. In contrast, the correlation is *negative* albeit insignificant for RJV_P, the risk due to positive or good jumps (row 3). In row 4, we include both RJV_N and RJV_P in the bivariate forecasting regression. Interestingly, the estimated coefficient on RJV_P increases substantially in magnitude to -1.05 from -0.70 in row 3; and more importantly, it becomes statistically significant at the 5% level. Similarly, the estimated coefficient on RJV_N increases sharply to 1.11 from 0.76 in row 2 and is now statistically significant at the 1% level. In addition, the adjusted R^2 of 3.1% in row 4 (where both RJV_N and RJV_P are included together) is noticeably higher than 1.1% in row 2 or 0.8% in row 3 (where RJV_N or RJV_P is included separately).

Because RJV_N and RJV_P positively correlate with each other (Table 1) but have opposite effects on conditional equity premium, the difference between the bivariate regression results in row 4 of Table 2 and the univariate regression results in rows 2 and 3 reflects an omitted variables problem, which attenuates the explanatory power of RJV_N and RJV_P in univariate regressions. These results highlight the asymmetric effects of negative and positive jumps on conditional equity premium.

In row 4 of Table 2, the coefficients on RJV_N (1.06) and RJV_P (-1.05) have similar magnitudes, and the Wald test fails to reject the null hypothesis that their absolute values are the same at the conventional significance level. Based on this empirical finding, we propose RJV_SIGNED, the difference between RJV_N and RJV_P, as a composite signed jump risk measure. Row 5 shows that RJV_SIGNED correlates positively and significantly with one-month-ahead excess market returns at the 1% level, with an adjusted R^2 of 3.4%. Consistent with the Wald test result, the estimated coefficient on RJV_SIGNED is 1.06, which is almost identical in magnitude to those on RJV_N and RJV_P reported in row 4.

Figure 2 shows that both RJV_P and RJV_N increase drastically during the 2001 stock market crash and the 2008 financial market crisis. One might suspect that our main findings reflect these unusual episodes in the second half sample. To address the concern, we investigate the relation between realized signed jump risk measures and future excess market returns using two subsamples of the January 1986 to December 1999 period and the January 2000 to December 2013 period, and find that results are qualitatively similar to those obtained using the full sample (untabulated). For example, RJV_SIGNED correlates positively and significantly with future equity premium in both half samples, with an estimated coefficient of 1.01 and 1.15 for the first and second subsamples, respectively. Therefore, the relation between realized signed jump risk measures and conditional equity premium is quite stable over time, and our results are not driven by any particular episode or outlier. Similarly, in the next subsection, we will show that realized signed jump risk measures have significant out-of-sample predictive power for excess market returns.

As a robustness check, we consider an alternative scheme for signing jumps following Andersen, Bollerslev, and Diebold (2007). When we detect a jump in a trading day, its sign is the same as that of the 5-minute interval return with the largest magnitude in that day. We also use an alternative jump detection method proposed by Lee and Mykland (2008) that allows for multiple jumps in a trading day. These alternative approaches result in qualitatively similar conclusion that realized negative or bad jump volatility correlates positively and significantly with future excess stock market returns. To converse space, we do not report these results but they are available upon request.

3.3 Out-of-Sample Forecasts

To address the potential data mining concern by Goyal and Welch (2008), in Table 3, we compare the out-of-sample performance of our proposed forecasting models with that of a benchmark model that uses the average historical equity premium as the forecast for the one-month-ahead equity premium. Over the January 1986 to December 2013 period, we use the observations from the first half sample period (January 1986 to December 1999) for the initial in-sample estimation, and then make recursive one-month-ahead out-of-sample forecasts for the remaining observations with an expanding sample. We use two statistics to gauge the out-of-sample forecast power. First, MSE_a/MSE_b is the ratio of the mean squared-forecasting-error of the forecasting model to that of the benchmark model. Second, ENC-NEW is the encompassing test proposed by Clark and McCraken (2001). It tests the null hypothesis that the benchmark model incorporates all the information about the next period's excess stock market return against the alternative hypothesis that realized jump risk measures provide additional information. As in Lettau and Ludvigson (2001), we use bootstrapped critical values obtained from 10,000 simulations for inferences.

In row 1 of Table 3, we use RJV_SIGNED as a predictor in the forecasting model. We find that RJV_SIGNED has significant out-of-sample predictive power. It has a smaller mean squared-forecasting-error than does the benchmark model, and the ENC-NEW test indicates that the difference in out-of-sample forecast performance is statistically significant at the 5% level. As a robustness check, we include both RJV_N and RJV_P as predictors in row 2 and find qualitatively similar results. To summarize, realized signed jump risk measures have significant out-of-sample forecasting power for excess market returns.

In addition, a simple trading strategy shows that the predictive power of signed jump risk measures is economically important. Specifically, we use the first half sample period (January 1986 to December 1999) for the initial in-sample estimation, and then make one-month-ahead out-of-sample forecasts for the remaining observations with an expanding sample. We consider a switching strategy of holding a market index for the next month if the predicted excess market return is positive, and hold the short-term Treasury bill otherwise. For comparison, we use the buy-and-hold of the market index as a benchmark strategy.

Table 4 shows that the excess return on the switching strategy based on RJV_SIGNED is 0.474% per month, noticeably higher than 0.456% for the buy-and-hold strategy. In addition, the standard deviation of returns on the switching strategy is 4.2%, which is lower than 4.8% for the buy-and-hold strategy. Overall, the Sharpe ratio of the switching strategy (11.3%) is about 20% higher than that of the buy-and-hold strategy (9.5%). Figure 3 illustrates visually the difference in performances of the two investment strategies. With an $100 initial investment, the value of the switching portfolio is higher than that of the buy-and-hold portfolio for most of the testing period. Similarly, the switching strategy based on RJV_N and RJV_P has a higher mean return (0.498%), a lower return volatility (4.3%), and an even higher Sharpe ratio (11.8%) than does the buy-and-hold strategy.

3.4 Control for Common Stock Market Return Predictors

Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011) show that variance risk premium (VRP) has a positive unconditional mean and predicts a rising excess stock market return. That is, stock market volatility is a priced risk factor that has significant effects on both variance risk premium and conditional equity premium. These authors offer two competing economic explanations for these important empirical findings. Bollerslev, Tauchen, and Zhou (2009) suggest that VRP reflects stochastic volatility of consumption volatility, while in the DY model it comes from jumps in conditional mean and volatility of consumption growth. As we will show in the next section, in the DY model, the realized signed jump volatility and variance risk premium have similar predictive power for excess market returns. Specifically, the latter always drives out the former in bivariate regressions of forecasting near-term equity premium in simulated data from the calibrated DY model. However, if we include stochastic volatility of volatility as an additional determinant of variance risk premium and conditional equity premium in an extended DY model, the realized signed jump volatility and variance risk premium contain independent information about future market returns. Therefore, our novel empirical findings allow us to shed light on economic forces underlying variance risk premium.

In Table 5, we compare the predictive power of variance risk premium with that of the realized signed jump volatility over the January 1990 to December 2013 period, during which we have data for both variables. We first replicate our main findings that RJV_SIGNED has significant forecasting power for one-month-ahead equity premium (row 1) but RJV does not (row 2) in this sample. Row 3 reproduces the Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011) finding that VRP correlates positively and significantly with future equity premium. To test whether or not RJV_SIGNED and VRP have similar predictive power, in row 4 of Table 5, we include them together in the forecasting regression. As in univariate regressions, both RJV_SIGNED and VRP have significantly positive effects on conditional equity premium. This result should not be a surprise because VRP correlates only moderately with realized jump risk measures; for example, the coefficient of its correlation with RJV_SIGNED is only 7% (untabulated). Our results indicates that jump risk is not the sole driver of variance risk premium. In the next section, we will propose an extended DY model that can replicate the finding in row 4 by allowing both stochastic volatility of volatility and jump risk to affect variance risk premium and conditional equity premium.

As an additional robustness check, in Table 5, we include commonly used market return predictors to the forecast regressions with (row 5) or without (row 6) the control for VRP. DP is the dividend yield; DEF is the difference in yields between BAA- and AAA-rated corporate bonds; TERM is the difference in yields between long-term and short-term Treasury bonds; and RREL is the stochastically detrended risk-free rate. Again, the positive correlation of RJV_SIGNED with future excess market returns remains significantly positive at least at the 5% level. These results suggest that in contrast with Goyal and Welch (2008), we find significant out-of-sample market return predictability because realized jump risk measures provide additional information about future excess market returns beyond that of the predictors examined by previous studies.

3.5 Longer Forecasting Horizons

In Table 6, we investigate the predictive power of signed realized jump risk measures over longer forecasting horizons. The effect of RJV_SIGNED on conditional equity premium is significantly positive at the 1% level for the 2-month horizon and at the 5% level for the 3-month horizon. It becomes marginally significant at the 10% level for the 6- and 12-month horizons. Similarly, the upper panel of Figure 4 shows that adjusted R^2 of RJV_SIGNED peaks at the 2-month horizon and then declines sharply with forecasting horizons. This pattern is somewhat different from the hump-shape R^2 pattern (peaking at the 4-month horizon and then declining gradually) for variance risk premium, as we show in the lower panel of Figure 4. We find qualitatively similar results when using RJV_N and RJV_P as forecasting variables. Jump risk measures have relatively short forecasting horizons because as we show in Table 1, they are not very persistent.

3.6 Downside Jump Risk and Aggregate Economic Activity

Risk-based asset pricing models imply a countercyclical conditional equity premium. If realized jump risk measures forecast excess market returns because they are a proxy of systematic risk, we expect that they correlate negatively with aggregate economic activity. Consistent with this conjecture, Figure 2 shows that RJV_P and especially, RJV_N, tend to increase substantially during business recessions. In Table 7, we address this issue formally by investigating the relation between signed realized jump risk measures and two important aggregate economic indicators—industrial production and the effective federal funds rate.[4] Industrial production is a direct measure of aggregate economic activity, and we expect a negative relation between realized jump risk measures and the future growth rate of industrial production. The Fed adopts a countercyclical monetary policy, i.e., eases the money when

[4]We find qualitatively similar results using the Chicago Fed National Activity Index.

the economy is weak and tights the money when the expected inflation rises. Hence the Fed is likely to lower the Federal funds rate when it senses that escalated jump risks pose a threat to economic growth. The Fed abandoned the federal funds rate as a monetary policy instrument when the effective policy rate reached its zero lower bound on December 16, 2008. Therefore, we investigate the relation between the effect federal funds rate and realized jump risk measures using the data up to December 2008.

Panel A of Table 7 shows that RJV_N correlates negatively with 1-, 2-, and 3-month ahead growth rates of industrial production at the 1% significance level even when we control for the lagged dependent variable. In contrast, the relation is much weaker and statistically insignificant for RJV_P. These results suggest that only bad/negative jumps have an adverse effect on aggregate economic growth. Similarly, Panel B shows that the Fed tends to lower the effective federal funds rate in response to increases in realized downside jump risk measures, and such a monetary policy reaction is statistically significant at the 1% level. In contrast, the Fed does not react to variations in realized good jump volatility. Similarly, the signed jump risk measure (RJV_SIGNED) has a negative effect on aggregate economic activity, and the effect is often statistically significant. Segal, Shaliastovich, and Yaron (2014) also find that downside macroeconomic uncertainty correlates negatively with future economic fundamentals; and they interpret this result by a long-run risk model with a feedback effect.

An increase in RJV_SIGNED represents a deterioration of investment opportunities. If a stock's return correlates positively with the contemporaneous change in RJV_SIGNED, the stock provides hedge for the jump risk and thus investors require a low risk premium for holding it. That is, we expect a negative correlation between loadings on RJV_SIGNED and the cross-section of future stock returns. To investigate this conjecture, we sort stocks equally into 10 portfolios by their loadings on RJV_SIGNED and find that, as hypothesized, stocks with high loadings have significantly lower future returns than stocks with low loadings even when we control for standard risk factors. Our results suggest that the realized signed jump risk measure is a pervasive risk factor that affects the cross section of expected stock returns. For brevity, we do not report these results here but they are available upon request.

4 Jump Risk in an Extended DY Model

Drechsler and Yaron (2011) characterize effects of jump risk on asset prices using a variant of the Bansal and Yaron (2004) long run risk model allowing for jumps in conditional mean and volatility of consumption growth. In the DY model, the realized signed jump risk measure and variance risk premium have similar predictive power for excess market returns. In contrast with this implication, as we show in Table 5, these two variables contain independent information about future equity premium in actual data, suggesting that jumps are not the only determinant of variance risk premium. To illustrate this point formally, we extend the DY model by including stochastic volatility of volatility as an additional determinant of both variance risk premium and conditional equity premium as in Bollerslev, Tauchen, and Zhou (2009). Under reasonable parameterizations, we show that the extended DY model accounts for the short-run joint predictability evidence of the realized signed jump risk measure and variance risk premium. Like the DY model, the extended DY model also implies asymmetric effects of jumps on conditional equity premium.

4.1 Model

In this subsection, we develop an extended DY model that embeds the DY model as a special case. Because our model is similar to the DY model, we provide only a brief explanation of its main features here and offer more details in Appendix A. The basic setup is a consumption-based asset pricing model with both stochastic volatility of volatility and jumps, and an representative agent has an Epstein and Zin (1989) recursive preference. The log pricing kernel at time $t+1$ is

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\Psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1}, \tag{10}$$

where c_{t+1} is log aggregate consumption, $r_{c,t+1}$ is the log return on the aggregate consumption claim, $0 < \delta < 1$ reflects the agent's time preference, $\theta = \frac{1-\gamma}{1-\frac{1}{\Psi}}$, γ is the coefficient of relative risk aversion, and Ψ is the elasticity of intertemporal substitution.

As in Drechsler and Yaron (2011), the vector of state variables $Y_t \in \mathtt{R}^n$ follows a VAR(1) process, which is driven by both Gaussian and compound Poisson jump shocks as follows:

$$Y_{t+1} = \mu + FY_t + G_t z_{t+1} + J_{t+1}. \tag{11}$$

The state vector and the first order dynamics are

$$Y_{t+1} = \begin{pmatrix} \Delta c_{t+1} \\ x_{t+1} \\ \overline{\sigma}^2_{t+1} \\ \sigma^2_{t+1} \\ q_{t+1} \\ \Delta d_{t+1} \end{pmatrix} \qquad F = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & \rho_x & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_{\overline{\sigma}} & 0 & 0 & 0 \\ 0 & 0 & (1-\rho_\sigma) & \rho_\sigma & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_q & 0 \\ 0 & \phi & 0 & 0 & 0 & 0 \end{pmatrix}. \tag{12}$$

$z_{t+1} = \left(z_{c,t+1}, z_{x,t+1}, z_{\overline{\sigma},t+1}, z_{\sigma,t+1}, z_{q,t+1}, z_{d,t+1} \right)' \sim N(0, I)$ is a vector of Gaussian shocks. $J_{t+1} = \left(0, J_{x,t+1}, 0, J_{\sigma,t+1}, 0, 0 \right)'$ is a vector of jump shocks, and the jump intensity is $\lambda_{x,t} = l_{1,x}\sigma_t^2$ and $\lambda_{\sigma,t} = l_{1,\sigma}\sigma_t^2$. The variance-covariance matrix of Gaussian shocks is $G_t G_t' = h + H_\sigma \sigma_t^2 + H_q q_t$. The constant term is $\mu = (I - F)E(Y_t)$.

State variables of the model economy include (1) consumption growth rate Δc_t, (2) expected consumption growth rate x_t, (3) long-run mean of consumption volatility $\overline{\sigma}_t^2$, (4) time-varying consumption volatility σ_t^2, (5) stochastic volatility of consumption volatility q_t, and (6) dividend growth rate Δd_t. The state variable q_t is similar to that in Bollerslev, Tauchen, and Zhou (2009) and Bollerslev, Xu, and Zhou (2013), and the other state variables are the same as those in Drechsler and Yaron (2011). That is, we extend the DY model by incorporating stochastic volatility of volatility q_t as an additional state variable.

The log conditional equity premium is:

$$\begin{aligned} \ln E_t(R_{m,t+1}) - r_{f,t} = {} & Br' h\Lambda + Br' H_\sigma \Lambda \sigma_t^2 + Br' H_q \Lambda q_t \\ & + \lambda_t'(\psi(Br) - 1) - \lambda_t'(\psi(Br - \Lambda) - \psi(-\Lambda)), \end{aligned} \tag{13}$$

where the market price of risk vector Λ and risk factor loading vector Br are specified in Appendix A. $\psi(u)$ is a vector with k'th component $\psi_k(u_k)$, and ψ_k is the moment-generating function (mgf) of the jump size ζ_k. As in Drechsler and Yaron (2011), the jump size has a demeaned Gamma distribution for $J_{x,t+1}$ and a Gamma distribution for $J_{\sigma,t+1}$.

Equation (13) shows that conditional equity premium has three time-varying components. The first component, $Br' H_\sigma \Lambda \sigma_t^2$, represents the classic positive risk-return tradeoff that conditional equity premium increases with conditional variance. The second component, $Br^{'}H_q\Lambda q_t$, is the premium for bearing volatility of volatility risk that depends positively on q_t. The third component, $\lambda_t'(\psi(Br)-1)-\lambda_t'(\psi(Br-\Lambda)-\psi(-\Lambda))$, measures the contribution from compound Poisson jump shocks. Because the jump intensity λ_t is a linear function of σ_t^2, this component also increases with conditional volatility. Overall, the log conditional equity premium is a linear function of σ_t^2 and q_t. In contrast, because Drechsler and Yaron (2011) do not consider stochastic volatility of volatility, the log conditional equity premium is a linear function of only σ_t^2 in their model.

Following Drechsler and Yaron (2011), we define variance risk premium as:

$$\begin{aligned} vp_{t,t+1} &\equiv E_t^Q[var_t^Q(r_{m,t+2})] - E_t^P[var_t^P(r_{m,t+2})] \\ &= Br^{'}H_\sigma Br[E_t^Q(\sigma_t^2) - E_t^P(\sigma_t^2)] + Br^{'}H_q Br[E_t^Q(q_t) - E_t^P(q_t)] \\ &\quad + Br^{2'}diag(\psi^{(2)}(-\Lambda))E_t^Q(\lambda_t) - Br^{2'}diag(\psi^{(2)}(0))E_t^P(\lambda_t). \end{aligned} \tag{14}$$

Like conditional equity premium, time-series variations in variance risk premium come from three sources: Consumption risk term related to σ_t^2; volatility uncertainty term related q_t; and jump risk term related to λ_t. Again, because the jump intensity is a linear function of conditional volatility, variance risk premium depends on σ_t^2 and q_t in the extended DY model and depends on σ_t^2 only in the DY model.

In the DY model, because the jump intensity is proportional to σ_t^2, realized jump risk volatility correlates positively with σ_t^2 and thus forecasts excess market returns. In a similar vein, variance risk premium predicts equity premium because of its correlation with σ_t^2. Therefore, realized jump risk volatility and variance risk premium contain similar information about conditional excess market returns in the DY model. By contrast, in the extended DY model, while realized jump risk volatility moves closely to σ_t^2, both variance risk premium and conditional equity premium depend on σ_t^2 and q_t. Therefore, realized jump risk premium and variance risk premium have independent information about future excess market returns, as we document in data (Table 5). We will illustrate these points using simulated data from both the DY model and the extended DY model.

4.2 Calibration

We calibrate the extended DY model to match three sets of economic and financial variables: (1) growth rates of consumption and dividends; (2) the equity premium and risk-free rate; and (3) variance risk premium. We use annual consumption and dividend data from 1930 to 2013. Per-capita consumption of nondurables and services are from NIPA. We construct per-share dividend series of the market index using CRSP data: The adjustment of dividends for share repurchase follows Bansal, Dittmar, and Lundblad (2005). We use CRSP value-weighted aggregate returns as the stock market return and 30-day T-bill returns as the risk-free rate; both are from CRSP over the 1930 to 2013 period. We construct monthly variance risk premium following Bollerslev, Tauchen, and Zhou (2009) for the January 1990 to December 2013 period. We generate 1000 sets of simulated data with the same sample size as that of actual data, and report the 5%, 50%, and 95% percentiles for each moment. Table 8 presents parameter values adopted in our calibrated model, which are in line with those used in Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011). Table 9 shows a close match in selected moments between actual data and simulated data.

4.3 Asymmetric Effects of Jumps on Conditional Equity Premium

In the extended DY model, the realized market return $r_{m,t+1}$ is:

$$r_{m,t+1} = r_0 + (Br'F - A'_m)Y_t + Br^{'}G_t z_{t+1} + Br'J_{t+1}. \tag{15}$$

Stock market return jumps $Br'J_{t+1}$ are due to jumps in x_t and σ_t^2. In simulated data, we define a good (bad) jump as the jump that causes a positive (negative) stock market return. Realized good (bad) jump volatility is the sum of absolute values of stock market returns due to good (bad) jumps. The realized signed jump risk measure is the difference between realized bad jump volatility and realized good jump volatility.

Using simulated data, we estimate regressions of forecasting excess market returns with signed jump risk measures. For direct comparison with actual data, the sample size of simulated data is equivalent to that in Table 5, which spans the January 1990 to December 2013 period. Table 10 reports the median values of 1,000 sets of simulation. It shows that the extended DY model accounts for asymmetric effects of jump risk on conditional equity premium. RJV_N always correlates positively and significantly with future excess market returns, while the correlation is always statistically insignificant for RJV_P.[5] Moreover, as we will show in the next subsection, RJV_SIGNED, the difference between RJV_N and RJV_P, correlates positively and significantly with conditional equity premium. Interestingly, consistent with our empirical findings reported in Table 6, the predictive power of signed jump risk measures concentrates at near terms, with R^2 peaking around the 6-month horizon in the extended DY model. This result reflects the fact that RJV_N and RJV_SIGNED are not persistent, with the median autocorrelation coefficient of 13% and 9%, respectively, in simulated data (untabulated). For comparison, we calibrate the DY model using the exactly same parameterizations adopted in Drechsler and Yaron (2011). Table 10 shows that the results are qualitatively similar for the DY model except that the predictive power is statistically insignificant for RJV_N at the 1-month horizon.

The asymmetry is due to jump size distributions in both models. Jumps in consumption volatility are always positive because they have a Gamma distribution. In calibrations, an increase in consumption volatility leads to an immediate fall in stock market prices; therefore, jumps in consumption volatility are bad jumps. Jumps in the expected consumption growth rate have a demeaned Gamma distribution and hence can take either a positive or a negative value. In addition, stock market prices depend positively on jumps in the expected consumption growth rate; therefore, these jumps can generate either a good or a bad jump. Overall, we observe more bad jumps than good jumps in simulated data; as a result, RJV_N has a closer correlation with conditional volatility than does RJV_P in finite samples. As we discuss above, realized jump risk volatility forecasts excess market returns due to its correlation with conditional volatility in both the DY model and the extended DY model.[6] Therefore, RJV_N has stronger predictive power for equity premium than does RJV_P.

[5]We find qualitatively similar results in univariate regressions. For brevity, they are not reported here but are available upon request.

[6]We verify this point using simulated data from both the DY model and the extended DY model.

4.4 Jump Risk and Variance Risk Premium

In this subsection, we investigate whether the extended DY model accounts for our empirical finding that the signed jump risk measure forecasts excess stock market returns even when we control for variance risk premium as an additional predictor. Again, we generate 1,000 sets of simulated data and report their median values in Table 11. Consistent with asymmetric effects of bad and good jump risks on conditional equity premium reported in Table 10, RJV_SIGNED—the difference between RJV_N and RJV_P, correlates positively and significantly with 1-month-ahead equity premium (row 2). We also replicate Drechsler and Yaron (2011) results that VRP is a significant market return predictor in row 1. Interestingly, both variables remain significantly positive in the bivariate regression (row 3). Results are qualitatively similar for the 3-month and 6-month forecasting horizons. In contrast, for the DY model, RJV_SIGNED has insignificant predictive power at the 5% level for short (1-month and 3-month) forecast horizons when we include VRP as a control variable.

The improvement of our extended DY model is consistent with our intuition that adding stochastic volatility of consumption volatility to the DY model can help characterize the short-run predictability pattern of both variance risk premium and jump risk. In particular, the signed jump risk measure as a risk factor impacts conditional equity premium through an independent, or a non-overlapping channel of that of variance risk premium. By design, the DY model intends to interpret variance risk premium and its predictability for equity premium as mainly driven by the joint jump dynamics in return and volatility. Therefore, it is not surprising that adding stochastic volatility-of-volatility breaks the near colinearity of variance risk premium and jump risk in forecasting stock market returns, especially at short forecasting horizons.[7]

[7] At the 6-month horizon, controlling for VRP weakens but does not eliminate the predictive power of RJV_SIGNED in the DY model. This is because neither VRP nor RJV_SIGNED has a perfect correlation with conditional volatility, the driver of conditional equity premium in the DY model.

4.5 Discussion

Tables 10 and 11 show that our main empirical results are broadly consistent with the extended DY model. The model, however, fails to account for the finding that RJV_P correlates negatively and significantly with future equity premium when in conjunction with RJV_N (row 4, Table 2). In particular, the median of estimated coefficients on RJV_P is always positive albeit statistically insignificant in Table 10. There are two possible explanations. First, the documented negative relation between RJV_P and conditional equity premium is due to small samples. We do observe the negative relation in some sets of simulated data. In actual data, the significant negative relation exists only in the second half sample (January 2000 to December 2013) but not the first half sample (January 1986 to December 1999). In contrast, the positive correlation of RJV_N or RJV_SIGNED with conditional equity premium is robust in both half samples.

Second, RJV_P indeed correlates negatively with conditional equity premium. We are unable to explain this potentially interesting relation using the DY model or the extended DY model, and recent studies have explored some tentative explanations. Segal, Shaliastovich, and Yaron (2014) point out that bad and good uncertainties have asymmetric effects on economic fundamentals. This view is consistent with the results reported in Table 7. Alternatively, Kilic and Shaliastovich (2015) assume asymmetric dependence of jump intensity on conditional volatility for good and bad jumps. While models built on these assumptions have some success in explaining data, a systematic investigation is warranted. Specifically, the relation between positive jump risk and conditional equity premium seems to be a promising topic for future research.

5 Concluding remarks

We document a novel empirical finding that realized jump risk, especially that associated with bad or negative jumps, is a significant determinant of conditional equity premium. In addition, information contents of realized jump risk about future equity premium are independent of those captured by variance risk premium that Drechsler and Yaron (2011) attribute to jump risk. Our results suggest that jump risk is not the sole determinant of variance risk premium. We illustrate this point by proposing an extended DY model allowing stochastic volatility of volatility to be an additional driver of both variance risk premium and conditional equity premium. Simulated data show that our main empirical findings are broadly consistent with the extended DY model.

References

Andersen, Toben G., Tim Bollerslev, and Francis X. Diebold (2007), "Roughing It Up: Including Jump Components in the Measurement, Modeling and Forecasting of Return Volatility," *Review of Economics and Statistics*, vol. 89, 701–720.

Andersen, Toben G., Tim Bollerslev, Francis X. Diebold, and Heiko Ebens (2001), "The Distribution of Realized Stock Return Volatility," *Journal of Financial Economics*, vol. 61, 43–76.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen (1997), "Empirical performance of alternative option pricing models," *Journal of Finance*, vol. 52, 2003–2049.

Bali, Turan G. and Armen Hovakimian (2009), "Volatility Spreads and Expected Stock Returns," *Management Science*, vol. 55, 1797–1812.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad (2005), "Consumption, Dividends, and the Cross Section of Equity Returns," *Journal of Finance*, vol. 60, 1639–1672.

Bansal, Ravi and Ivan Shaliastovich (2011), "Learning and Asset-price Jumps," *Review of Financial Studies*, vol. 24, 2738–2780.

Bansal, Ravi and Amir Yaron (2004), "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance*, vol. 59, 1481–1509.

Barndorff-Nielsen, Ole E. and Neil Shephard (2002), "Econometric Analysis of Realized Volatility and its Use in Estimating Stochastic Volatility Models," *Journal of the Royal Statistical Society*, vol. 64, 253–280.

Barndorff-Nielsen, Ole E. and Neil Shephard (2004), "Power and Bipower Variation with Stochastic Volatility and Jumps," *Journal of Financial Econometrics*, vol. 2, 1–37.

Barndorff-Nielsen, Ole E. and Neil Shephard (2006), "Econometrics of Testing for Jumps in Financial Economics using Bipower Variation," *Journal of Financial Econometrics*, vol. 4, 1–30.

Barro, Robert J. (2006), "Rare Disasters and Asset Markets in the Twentieth Century," *Quarterly Journal of Economics*, vol. 121, 823–866.

Bates, David S. (1996), "Jumps and Stochastic Volatility: Exchange Rate Processes Implicit in Deutsch Mark Options," *Review of Financial Studies*, vol. 9, 69–107.

Bates, David S. (2008), "The Market for Crash Risk," *Journal of Economic Dynamics and Control*, vol. 32, 2291–2321.

Becker, Ralf, Adam E. Clement, and Andrew McClelland (2009), "The Jump Component of S&P 500 Volatility and the VIX Index," *Journal of Banking and Finance*, vol. 33, 1033–1038.

Bollerslev, Tim, George Tauchen, and Hao Zhou (2009), "Expected Stock Returns and Variance Risk Premia," *Review of Financial Studies*, vol. 101, 552–573.

Bollerslev, Tim and Viktor Todorov (2011), "Tails, Fears, and Risk Premia," *Journal of Finance*, vol. 66-6, 2165–2211.

Bollerslev, Tim, Viktor Todorov, and Lai Xu (2014), "Tail Risk Premia and Return Predictability," Working Paper, Duke University .

Bollerslev, Tim, Lai Xu, and Hao Zhou (2013), "Stock Return and Cash Flow Predictability: The Role of Volatility Risk," *Journal of Econometrics forthcoming*.

Broadie, Mark, Mikhail Chernov, and Michael Johannes (2007), "Model Specification and Risk Premia: Evidence from Futures Options," *Journal of Finance*, vol. 62, 1453–1490.

Campbell, John Y. and Robert J. Shiller (1988), "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, vol. 1, 195–228.

Clark, Todd E. and Michael W. McCraken (2001), "Test of Equal Forecast Accuracy and Encompassing For Nested Models," *Journal of Econometrics*, vol. 105-1, 85–110.

Cremers, Martijin, Michael Halling, and David Weinbaum (2011), "In Search of Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns," Working Paper.

Drechsler, Itamar and Amir Yaron (2011), "What's Vol Got to Do with It," *Review of Financial Studies*, vol. 24, 1–45.

Du, Du (2011), "General Equilibrium Pricing of Options with Habit Formation and Event Risks," *Journal of Financial Economics*, vol. 99, 400–426.

Du, Jian and Nikunj Kapadia (2012), "The Tail in the Volatility Index," U. Massachusetts, Amherst Working paper.

Dungey, Mardi, Michael Mckenzie, and L. Vanessa Smith (2009), "Empirical Evidence on Jumps in the Term Structure of the U. S. Treasury Market," *Journal of Empirical Finance*, vol. 16, 430–445.

Epstein, Larry G. and Stanley E. Zin (1989), "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, vol. 57, 937–969.

Eraker, Bjørn (2004), "Do Stock Prices and Volatility Jump ? Reconciling Evidence from Spot and Option Prices," *Journal of Finance*, vol. 59, 1367–1403.

Eraker, Bjørn and Ivan Shaliastovich (2008), "An Equilibrium Guide to Designing Affine Pricing Models," *Mathematical Finance*, vol. 18, 519–543.

Feunou, Bruno, Mohammad R. Jahan-Parvar, and Romeo Tedongap (2012), "Modeling Market Downside Volatility," *Review of Finance*, vol. 17, 443–481.

Gabaix, Xavier (2012), "Variable Rare Disasters: An Exactly Solved Model for Ten Puzzles in Macro-Finance," *Quarterly Journal of Economics*, vol. 127, 645–700.

Goyal, Amit and Ivo Welch (2008), "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction," *Review of Financial Studies*, vol. 21, 1455–1508.

Guo, Hui and Robert F. Whitelaw (2006), "Uncovering the Risk-Return Relation in the Stock Market," *Journal of Finance*, vol. 61, 1433–1463.

Huang, Xin and George Tauchen (2005), "The Relative Contribution of Jumps to Total Price Variance," *Journal of Financial Econometrics*, vol. 3, 456–499.

Jiang, George J., Ingrid Lo, and Adrien Verdelhan (2011), "Information Shocks, Liquidity Shocks, Jumps, and Price Discovery: Evidence from the U. S.Treasury Market," *Journal of Financial and Quantitative Analysis*, vol. 46, 527–551.

Jiang, George J. and Tong Yao (2013), "Stock Price Jumps and Cross-Sectional Return Predictability," *Journal of Financial and Quantitative Analysis*, vol. 48, 1519–1544.

Kelly, Bryan and Hao Jiang (2014), "Tail Risk and Asset Prices," *Review of Financial Studies*, vol. 27, 2841–2871.

Kilic, Mete and Ivan Shaliastovich (2015), "Good and Bad Variance Premium and Expected Returns," Wharton Working Paper.

Lahaye, Jerome, Sebastien Laurent, and Chritopher J. Neely (2011), "Jumps, Cojumps and Macro Announcements," *Journal of Applied Econometrics*, vol. 26, 893–921.

Lee, Suzenne S. and Per A. Mykland (2008), "Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics," *Review of Financial Studies*, vol. 21, 2535–2563.

Lettau, Martin and Sydney Ludvigson (2001), "Consumption, Aggregate Wealth, and Expected Stock Returns," *Journal of Finance*, vol. 56, 815–849.

Liu, Jun, Jun Pan, and Tan Wang (2005), "An Equilibrium Model of Rare-Event Premia and Its Implication for Option Smirks," *Review of Financial Studies*, vol. 18, 131–164.

Longstaff, Francis A. and Monika Piazzesi (2004), "Corporate Earnings and the Equity Premium," *Journal of Financial Economics*, vol. 74, 401–421.

Mehra, Rajnish and Edward C. Prescott (1988), "The Equity Risk Premium: A Solution?" *Journal of Monetary Economics*, vol. 18, 133–136.

Merton, Robert C. (1976), "Option Pricing when Underlying Stock Returns Are Discontinuous," *Journal of Financial Economics*, vol. 3, 125–144.

Pan, Jun (2002), "The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study," *Journal of Financial Economics*, vol. 63, 3–50.

Patton, Andrew J. and Kevin Sheppard (2013), "Good Volatility, Bad Volatility: Signed Jumps and the Persistence of Volatility," Working Paper, Duke University .

Rietz, Thomas A. (1988), "The Equity Risk Premium: A Solution," *Journal of Monetary Economics*, vol. 22, 117–131.

Santa-Clara, Pedro and Shu Yan (2010), "Crashes, Volatility, and the Equity Premium: Lessons from S&P500 Options," *Review of Economics and Statistics*, vol. 92, 435–451.

Segal, Gill, Ivan Shaliastovich, and Amir Yaron (2014), "Good and Bad Uncertainty: Macroeconomic and Financial Market Implications," Working Paper .

Tauchen, George and Hao Zhou (2011), "Realized Jumps on Financial Markets and Predicting Credit Spreads," *Journal of Econometrics*, vol. 160-1, 102–118.

Wachter, Jessica A. (2013), "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?" *Journal of Finance*, vol. 68, 987–1035.

Wright, Jonathan H. and Hao Zhou (2009), "Bond Risk Premia and Realized Jump Risk," *Journal of Banking and Finance*, vol. 33, 2333–2345.

Yan, Shu (2011), "Jump Risk, Stock Returns, and Slope of Implied Volatility Smile," *Journal of Financial Economics*, vol. 99, 216–233.

Zhang, Benjamin Yibin, Hao Zhou, and Haibin Zhu (2009), "Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms," *Review of Financial Studies*, vol. 22, 5109–5131.

Appendix

A Model solution

A.1 Model Specification

The jump intensity $\lambda_t = l_{1,\sigma}\sigma_t^2$ has an affine structure in which the intensity is proportional to the consumption volatility. The size of the jump in σ_t^2 follows a Gamma distribution, i.e. $\zeta_\sigma \sim \Gamma\left(\nu_\sigma, \frac{\mu_\sigma}{\upsilon_\sigma}\right)$, and the size of jump in x_t follows the negative of the demeaned Gamma distribution, i.e. $\zeta_x \sim -\Gamma\left(\upsilon_x, \frac{\mu_x}{\nu_x}\right) + \mu_x$. Following Drechsler and Yaron (2011), we subtract the conditional mean of jump size from its realized value to obtain the true "jump innovations".

The VAR constant term μ equals $(I - F)\, E\,(Y_t)$. Without loss of generality, we adopt the normalization condition that $E\left[\sigma_t^2\right] = E\left[\overline{\sigma}_t^2\right] = 1$. We set the expectation of q_t to be 10 and the magnitude of q_t/σ_t^2 ratio is thus similar to that in Bollerslev, Tauchen, and Zhou (2009).

Finally, we parameterize the variance-covariance matrix of the Gaussian shocks by specifying h, H_σ and H_q as following:

$$h = \begin{pmatrix} h_c & 0 & 0 & 0 & 0 & h_{cd} \\ 0 & h_x & 0 & 0 & 0 & 0 \\ 0 & 0 & h_{\overline{\sigma}} & 0 & 0 & 0 \\ 0 & 0 & 0 & h_\sigma & 0 & 0 \\ 0 & 0 & 0 & 0 & h_q & 0 \\ h_{cd} & 0 & 0 & 0 & 0 & h_d \end{pmatrix} \tag{A.1}$$

where $h_j = \varphi_j^2(1-\omega_j)$, $j \in \{c, x, \overline{\sigma}, \sigma, q, d\}$ and $h_{cd} = \varphi_c\varphi_d\sqrt{1-\omega_c}\sqrt{1-\omega_d}\Omega_{cd}$

$$H_\sigma = \begin{pmatrix} \varphi_c^2\omega_c & 0 & 0 & 0 & 0 & \varphi_c\varphi_d\sqrt{\omega_c}\sqrt{\omega_d}\Omega_{cd} \\ 0 & \varphi_x^2\omega_x & 0 & 0 & 0 & 0 \\ 0 & 0 & \varphi_{\overline{\sigma}}^2\omega_{\overline{\sigma}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \varphi_c\varphi_d\sqrt{\omega_c}\sqrt{\omega_d}\Omega_{cd} & 0 & 0 & 0 & 0 & \varphi_d^2\omega_d \end{pmatrix} \tag{A.2}$$

$$H_q = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \varphi_\sigma^2 \omega_\sigma & 0 & 0 \\ 0 & 0 & 0 & 0 & \varphi_q^2 \omega_q & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{A.3}$$

We keep the shock structure in Bansal and Yaron (2004) and Drechsler and Yaron (2011) by setting $\omega_x = 1, \omega_\sigma = 1$ and $\omega_{\overline{\sigma}} = 0$. We also assume q_t follows a square-root or CIR process and set $\omega_q = 1$. Ω_{cd} captures the correlation between the consumption growth and dividend.

A.2 Model Solution

Using the log-linearization method (Campbell and Shiller, 1988), we get the linearized $r_{c,t+1}$ around the unconditional mean of v_t :

$$r_{c,t+1} \approx K_0 + K_1 v_{t+1} - v_t + \Delta c_{t+1} \tag{A.4}$$

where $K_1 = \frac{e^{E(v)}}{1+e^{E(v)}}$ and $K_0 = \ln(1 + e^{E(v)}) - K_1 E(v)$

Following the approach taken by Bansal and Yaron (2004), Eraker and Shaliastovich (2008) and Drechsler and Yaron (2011), we conjuncture that the no-bubbles solution for the log wealth-consumption ratio is affine in the state vector:

$$v_t = A_0 + A^{'} Y_t \tag{A.5}$$

where $A = (A_c, A_x, A_{\overline{\sigma}}, A_\sigma, A_q, A_d)^{'}$ is a vector of pricing coefficients, A_0 is a constant, and $A_c = A_d = 0$. For the simplification of system equations, we define the same $f(u)$ and $g(u)$ functions as those in Drechsler and Yaron (2011):

For $u \in \mathtt{R}^n$:

$$f(u) = \mu^{'} u + \frac{1}{2} u^{'} h u \tag{A.6}$$

$$g(u) = F^{'} u + \frac{1}{2} u^{'} H_\sigma u + \frac{1}{2} u^{'} H_q u + l_1^{'}(\psi(u) - 1) \tag{A.7}$$

Then we get the following system of $n+1$ equations in A_0 and A:

$$0 = \theta \ln \delta + \theta k_0 + \theta(k_1 - 1) A_0 + f(\theta(1 - \frac{1}{\Psi}) e_c + \theta k_1 A) \tag{A.8}$$

$$0 = g(\theta(1 - \frac{1}{\Psi}) e_c + \theta k_1 A) - A\theta \tag{A.9}$$

A and A_0 can be solved for jointly with K_0 and K_1 by adding equations to the system in Equations (12) and (13).

By substituting v_t into the Euler equation, we get the equilibrium solutions for the volatility-of-volatility pricing coefficient A_q, which is expressed as

$$A_q = \frac{(1-\rho_q K_1)\theta + \sqrt{\theta^{2(1-\rho_q K_1)^2 - (\theta K_1)^4 \varphi_q^2 \omega_q \varphi_\sigma^2 \omega_\sigma A_\sigma^2}}}{(\theta K_1)^2 \varphi_q^2 \omega_q} \tag{A.10}$$

To study the variance premium, equity risk premium, and their relationship, we also need to solve for the market return. Similarly, we log-linearize the return on the market, $r_{m,t+1}$, around the unconditional mean of $v_{m,t+1}$:

$$r_{m,t+1} \approx K_{0,m} + K_{1,m} v_{m,t+1} - v_{m,t} + \Delta d_{t+1} \tag{A.11}$$

Then, we conjecture the log price-dividend ratio:

$$v_{m,t} = A_{0.m} + A_m^{'} Y_t \tag{A.12}$$

where $A_m = (A_{c,m}, A_{x,m}, A_{\overline{\sigma},m}, A_{\sigma,m}, A_{q,m}, A_{d,m})^{'}$ is the vector of pricing coefficients for the market. It is also the case that $A_{c,m} = A_{d,m} = 0$. To get the $A_{0,m}$ and A_m, we solve the following system of equations:

$$0 = \theta \ln \delta - (1-\theta)(K_1 - 1)A_0 - (1-\theta)K_0 + K_{0,m} + (K_{1,m} - 1)A_{0,m} + f(e_d + K_{1,m}A_m - \Lambda) \tag{A.13}$$

$$0 = g(e_d + K_{1,m}A_m - \Lambda) + (1-\theta)A - A_m \tag{A.14}$$

where $\Lambda = (\gamma, K_1 A_x(1-\theta), K_1 A_{\overline{\sigma}}(1-\theta), K_1 A_\sigma(1-\theta), K_1 A_q(1-\theta), 0)^{'}$ can be interpreted as the price of risk for Gaussian shocks.

We also get the equilibrium solutions for $A_{q,m}$:

$$A_{q,m} = \frac{-b + \sqrt{b^2 - 4ac}}{2a} \tag{A.15}$$

where $a = 0.5\varphi_q^2 \omega_q K_{1m}^2; b = \left[(1-\rho_q)K_{1m} - (1-\theta)K_1 A_q K_{1m} \varphi_q^2 \omega_q\right];$
$c = 0.5\varphi_q^2 \omega_q (1-\theta)^2 K_1^2 A_q^2 - (1-\rho_q)(1-\theta)K_1 A_q + 0.5\left[K_{1m}A_{\sigma,m} - (1-\theta)K_1 A_\sigma\right]^2 \varphi_\sigma^2 \omega_\sigma$

As discussed in Bollerslev, Tauchen and Zhou (2009), the specific roots must imply $\varphi_q^2 \omega_q A_q A_{q,m} \to 0$ for $\varphi_q \to 0$, which guarantees that the premium disappears when q_t is constant. In our numerical solution, we try the four pairs of solution $(A_q, A_{q,m})$. Only one pair used in our paper satisfies the convergence condition.

The model implied log equity premium can thus be written as:

$$\ln E_t(R_{m,t+1}) - r_{f,t} = Br^{'} h \Lambda + Br^{'} H_\sigma \Lambda \sigma_t^2 + Br^{'} H_q \Lambda q_t + \lambda_t^{'}(\psi(Br) - 1) - \lambda_t^{'}(\psi(Br - \Lambda) - \psi(-\Lambda)) \tag{A.16}$$

where$Br = (0, K_{1m}A_{x,m}, K_{1m}A_{\overline{\sigma},m}, K_{1m}A_{\sigma,m}, K_{1m}A_{q,m}, 1)$; and $\psi(u)$ is the vector with kth component $\psi_k(u_k)$, ψ_k is the moment-generating function (mgf) of the jump size ζ_k.

Table 1: Summary Statistics

	ERET	RJV	RJV_N	RJV_P	RJV_SIGNED
	Panel A: Univariate Statistics				
Mean	0.646	1.062	0.461	0.600	-0.139
SD	4.564	1.135	0.722	0.680	0.824
AR(1)	0.090	0.410	0.348	0.216	0.050
	Panel B: Cross-Correlation				
ERET	1.000				
RJV	-0.078	1.000			
RJV_N	-0.135	0.822	1.000		
RJV_P	0.014	0.796	0.310	1.000	
RJV_SIGNED	-0.130	0.064	0.621	-0.553	1.000

Note: The table presents summary statistics of selected variables. ERET is the excess stock market return. RJV is the realized volatility due to jumps. RJV_N is the realized volatility due to negative jumps. RJV_P is the realized volatility due to positive jumps. RJV_SIGNED is the difference between RJV_N and RJV_P. The sample spans the January 1986 to December 2013 period.

Table 2: Forecasting Monthly Excess Returns Using Realized Jump Volatility

	RJV	RJV_N	RJV_P	RJV_SIGNED	Wald-Test (p-value)	R^2
1	0.056					-0.281
	(0.282)					
2		0.757**				1.140
		(0.346)				
3			-0.702			0.794
			(0.506)			
4		1.064***	-1.053**		0.000	3.072
		(0.388)	(0.508)		(0.983)	
5				1.059***		3.363
				(0.372)		

Note: This table presents the OLS estimation results for forecasting one-month-ahead excess market returns using realized jump risk measures. RJV is the realized volatility due to jumps. RJV_N is the realized volatility due to negative jumps. RJV_P is the realized volatility due to positive jumps. RJV_SIGNED is the difference between RJV_N and RJV_P. We also report the adjusted-R^2s. Newey-West standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample spans the January 1986 to December 2013 period.

Table 3: Out-of-Sample Forecast Tests

	Models	MSE_a/MSE_b	ENC-NEW		
			Statistic	10% C.V.	5% C.V.
1	C+RJV_SIGNED v.s. C	0.975	8.040	1.016	1.628
2	C+RJV_N+RJV_P v.s. C	0.986	7.592	1.592	2.386

Note: The table compares the out-of-sample performance of our proposed forecasting models (C+RJV_SIGNED and C+RJV_N+RJV_P) with that of a benchmark model that uses the average equity premium in historical data as the forecast for the one-month-ahead equity premium (C). Over the January 1986 to December 2013 period, we use the observations from the first half sample period (January 1986 to December 1999) for the initial in-sample estimation, and then make recursive one-month-ahead out-of-sample forecasts for the remaining observations with an expanding sample. We use two statistics to gauge the out-of-sample forecast power. First, MSE_a/MSE_b is the ratio of the mean squared-forecasting-error of the forecasting model to that of the benchmark model. Second, ENC-NEW is the encompassing test proposed by Clark and McCracken (2001). We use bootstrapped critical values (C.V.) obtained from 10,000 simulations for inferences.

Table 4: Economic Performance of Switching Strategy

	Mean Excess Return	Standard Deviation	Sharpe Ratio
Buy-and-Hold	0.456%	0.048	0.095
RJV_SIGNED	0.474%	0.042	0.113
RJV_N+RJV_P	0.498%	0.042	0.118

Note: This table report performance of the switching strategy using RJV_SIGNED or RJV_N+RJV_P as market timing indicators. We hold a market index for the next month if the predicted excess market return is positive and hold the short-term Treasury bill otherwise. We use the first half sample (January 1986 to December 1999 for the initial in-sample forecast regression, and make out-of-sample forecasts recursively for the second half sample (January 2000 to December 2013). For comparison, we also report the performance of the buying-and-holding market index strategy.

Table 5: Control for Variance Risk Premium and Other Commonly Used Predictors

	RJV_SIGNED	RJV	VRP	DP	DEF	TERM	RREL	R^2
1	0.916**							2.899
	(0.388)							
2		-0.238						-0.183
		(0.662)						
3			0.051***					5.159
			(0.011)					
4	0.835**		0.049***					7.520
	(0.397)		(0.011)					
5	0.840**		0.053***	0.018*	-0.569	0.070	7.400**	9.034
	(0.423)		(0.011)	(0.010)	(0.946)	(0.223)	(3.353)	
6	1.085***			0.015**	-0.664	-0.015	2.368	3.544
	(0.392)			(0.007)	(1.256)	(0.197)	(3.755)	

Note: The table reports the OLS estimation results of forecasting one-month-ahead excess market returns. RJV_SIGNED is the difference between realized volatilities due to negative and positive jumps. VRP is variance risk premium. DP is the dividend yield. DEF is the default risk premium computed as the difference in yields between BAA- and AAA-rated corporate bonds. TERM is the difference in yields between long-term and short-term Treasury bonds. RREL is the stochastically detrended risk-free rate. The monthly data span the January 1990 to December 2013 period for which we have variance risk premium data. Newey-West standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Forecasting Excess Returns over Longer Horizons

	RJV_SIGNED	RJV	RJV_N	RJV_P	J-Test (p-value)	R^2
			Panel A: 2 Months			
1	1.602***					3.557
	(0.584)					
2		-0.144				-0.220
		(0.497)				
3			1.268**	-1.882**	0.408	3.454
			(0.658)	(0.780)	(0.523)	
			Panel B: 3 Months			
4	1.373**					2.591
	(0.618)					
5		-0.430				0.676
		(0.436)				
6			1.030	-1.783**	0.624	1.562
			(0.731)	(0.856)	(0.429)	
			Panel C: 6 Months			
7	1.545*					0.909
	(0.852)					
8		-0.173				0.035
		(0.223)				
9			1.111	-2.065*	0.403	0.823
			(1.077)	(1.183)	(0.526)	
			Panel D: 12 Months			
10	1.911*					0.638
	(1.015)					
11		0.034				-0.281
		(0.153)				
12			2.548*	-1.143	0.317	0.567
			(1.543)	(1.637)	(0.573)	

Note: The table reports the OLS estimation results of forecasting excess market returns at difference forecast horizons. RJV_N is the realized volatility due to negative jumps. RJV_P is the realized volatility due to positive jumps. RJV_SIGNED is the difference between RJV_N and RJV_P. The monthly data span the January 1986 to December 2013 period. Newey-West standard errors are in parentheses except p-value for the J-test. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Realized Jump Risks and Future Economic Activity

RJV_SIGNED	RJV_N	RJV_P	LAG	R^2
Panel A: Forecasting Industrial Production (1986-2013)				
1 Month				
-0.112*			0.224**	6.278
(0.059)			(0.099)	
	-1.606***	0.052	0.203**	6.894
	(0.060)	(0.071)	(0.098)	
2 Months				
-0.205**			0.545***	13.986
(0.097)			(0.144)	
	-0.292***	0.097	0.507***	14.927
	(0.100)	(0.118)	(0.144)	
3 Months				
-0.209			0.873***	17.632
(0.101)			(0.211)	
	-0.346***	-0.039	0.814***	18.991
	(0.117)	(0.120)	(0.211)	
Panel B: Forecasting Federal Funds Rate(1986-2008)				
1 Month				
-1.529			0.526***	27.038
(1.074)			(0.076)	
	-3.280***	-1.213	0.509***	28.095
	(1.459)	(1.488)	(0.077)	
2 Months				
-4.956***			0.899***	26.464
(2.382)			(0.170)	
	-8.141***	-0.031	0.868***	27.637
	(2.382)	(3.291)	(0.171)	
3 Months				
-8.468***			1.258***	27.384
(2.988)			(0.241)	
	-11.814***	3.230	1.226***	27.943
	(3.742)	(4.516)	(0.241)	

Note: The table reports the OLS estimation results of forecasting changes in aggregate economic activity using realized jump risk measures. RJV_N is the realized volatility due to negative jumps. RJV_P is the realized volatility due to positive jumps. The monthly data span the January 1986 to December 2013 period in Panel A and the January 1986 to December 2008 period in Panel B. Newey-West standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Calibration-Model Parameters

Preferences	δ	γ	Ψ				
	0.9983	10	2.95				
$\triangle c_{t+1}$	$E[\triangle c]$	φ_c	ω_c	ω_{cd}			
	0.0016	0.0058	0.5	0.2			
x_{t+1}	$E[x]$	ρ_x	φ_x	ω_x	$l_{1,\sigma}(x)$	μ_x	ν_x
	0	0.976	$0.032\times\varphi_c$	1	0.4/12	$3.188\times\varphi_x$	1
$\overline{\sigma}^2_{t+1}$	$E[\overline{\sigma}^2]$	$\rho_{\overline{\sigma}}$	$\varphi_{\overline{\sigma}}$	$\omega_{\overline{\sigma}}$			
	1	0.985	0.05	0			
σ^2_{t+1}	$E[\sigma^2]$	ρ_σ	φ_σ	ω_σ	$l_{1,\sigma}(\sigma)$	μ_σ	ν_σ
	1	0.87	0.12	1	0.4/12	5.015	1
q_{t+1}	$E[q]$	ρ_q	φ_q	ω_q			
	10	0.13	1	1			
$\triangle d_{t+1}$	$E[\triangle d]$	ϕ	φ_d	ω_d			
	0.0016	2.5	$5.7\times\varphi_c$	0.125			

Note: The table presents the parameters used in calibration. We consider an extended version of the Drechsler and Yaron (2011) model with (1) jumps in both return and volatility and (2) stochastic volatility-of-volatility as in Bollerslev et al. (2009). See Section 4.1. for details.

Table 9: Calibration Results

Statistic	Data	Model		
	Est.	5%	50%	95%
Cash Flow Dynamics				
$E[\triangle c]$	1.80	1.16	1.92	2.70
$\sigma[\triangle c]$	2.20	1.75	2.16	2.83
$AC1(\triangle c)$	0.50	0.21	0.42	0.60
$E[\triangle d]$	0.90	-0.55	2.04	4.83
$\sigma[\triangle d]$	13.2	8.68	9.99	11.70
$AC1(\triangle d)$	0.11	0.10	0.28	0.45
$corr(\triangle c, \triangle d)$	0.55	0.10	0.31	0.52
Returns				
$E[r_m]$	7.57	4.40	6.89	9.66
$E[r_f]$	0.68	0.62	1.30	1.72
$\sigma(r_m)$	19.7	12.97	16.60	24.34
$\sigma(r_f)$	1.89	0.85	1.81	3.64
Variance Premium				
$\sigma(var_t(r_m))$	37.46	8.02	28.11	92.50
$AC1(var_t(r_m))$	0.74	0.60	0.75	0.90
$AC2(var_t(r_m))$	0.59	0.34	0.56	0.81
$E[VP]$	18.46	18.38	30.63	70.33
$\sigma[VP]$	20.34	12.00	42.06	138.39
$skew(VP)$	3.74	1.97	3.78	5.87
$kurt(VP)$	26.78	8.49	20.38	44.19

Note: The table presents moments of consumption, dividend, asset-pricing and variance premium from data and models. Consumption, dividend, and asset price data are real, sampled at the annual frequency, and cover the 1930 to 2013 period. Variance risk premium data are sampled at the monthly frequency and cover the January 1990 to December 2013 period. We report percentiles of these statistics based on 1,000 sets of simulated data, with each statistic calculated using a sample size equals to its data counterpart.

Table 10: Calibration Based Forecasting with RJV_P and RJV_N

		DY Model		Extended DY Model	
		RJV_P	RJV_N	RJV_P	RJV_N
	One Month				
1	β	3.02	2.53	4.77	3.16
	t-stat	0.64	1.56	0.74	2.50
	R^2	0.02		0.04	
	Three Month				
2	β	2.49	2.24	4.06	2.55
	t-stat	0.87	2.40	1.04	3.70
	R^2	0.04		0.07	
	Six Month				
3	β	1.88	1.87	3.12	1.99
	t-stat	1.05	2.78	1.23	4.25
	R^2	0.05		0.10	
	Twelve Month				
4	β	1.20	1.25	2.08	1.29
	t-stat	1.01	2.92	1.21	4.69
	R^2	0.05		0.09	

Note: The table presents the OLS estimation for the slope β, R^2, and the t-statistics from the predictive regression of equity premium on RJV_P and RJV_N using simulated data. The left panel is the DY model, and the right panel is the extended DY model. Simulated data are sampled at the monthly frequency and the sample size is equivalent to the January 1990 to December 2013 period as in Table 5. For brevity, We report only the 50 percentile of estimation results obtained from 1,000 sets of simulated data.

Table 11: Calibration Based Forecasting for Equity Premium

		DY Model		Extended DY Model	
		VRP	RJV_SIGNED	VRP	RJV_SIGNED
	One Month				
1	β	0.65		0.25	
	t-stat	2.48		3.26	
	R^2	0.02		0.04	
2	β		2.28		3.05
	t-stat		1.45		2.44
	R^2		0.01		0.03
3	β	0.61	1.65	0.23	2.65
	t-stat	2.10	0.97	2.75	2.01
	R^2	0.04		0.07	
	Three-Month				
4	β	0.56		0.21	
	t-stat	2.68		3.79	
	R^2	0.05		0.09	
5	β		2.03		2.49
	t-stat		2.21		3.60
	R^2		0.02		0.06
6	β	0.50	1.45	0.19	2.02
	t-stat	2.39	1.71	3.37	3.05
	R^2	0.07		0.13	
	Six-Month				
7	β	0.45		0.16	
	t-stat	2.86		4.11	
	R^2	0.07		0.11	
8	β		1.67		1.93
	t-stat		2.68		4.24
	R^2		0.03		0.08
9	β	0.40	1.22	0.14	1.52
	t-stat	2.59	2.23	3.79	3.94
	R^2	0.09		0.17	

Note: The table presents the OLS estimation for the slope β, R^2, and the t-statistics from the predictive regression of equity premium on variance premium (VRP) and the signed jump risk measure (RJV_SIGNED) using simulated data. The left panel is the DY model, and the right panel is extended DY model. Simulated data are sampled at the monthly frequency, and the sample size is equivalent to the January 1990 to December 2013 period as in Table 5. For each forecasting horizon, we report results for (1) univariate regressions that include only one predictor and (2) bivariate regressions that include both variables. For brevity, We report only the 50 percentile of estimation results obtained from 1,000 sets of simulated data.

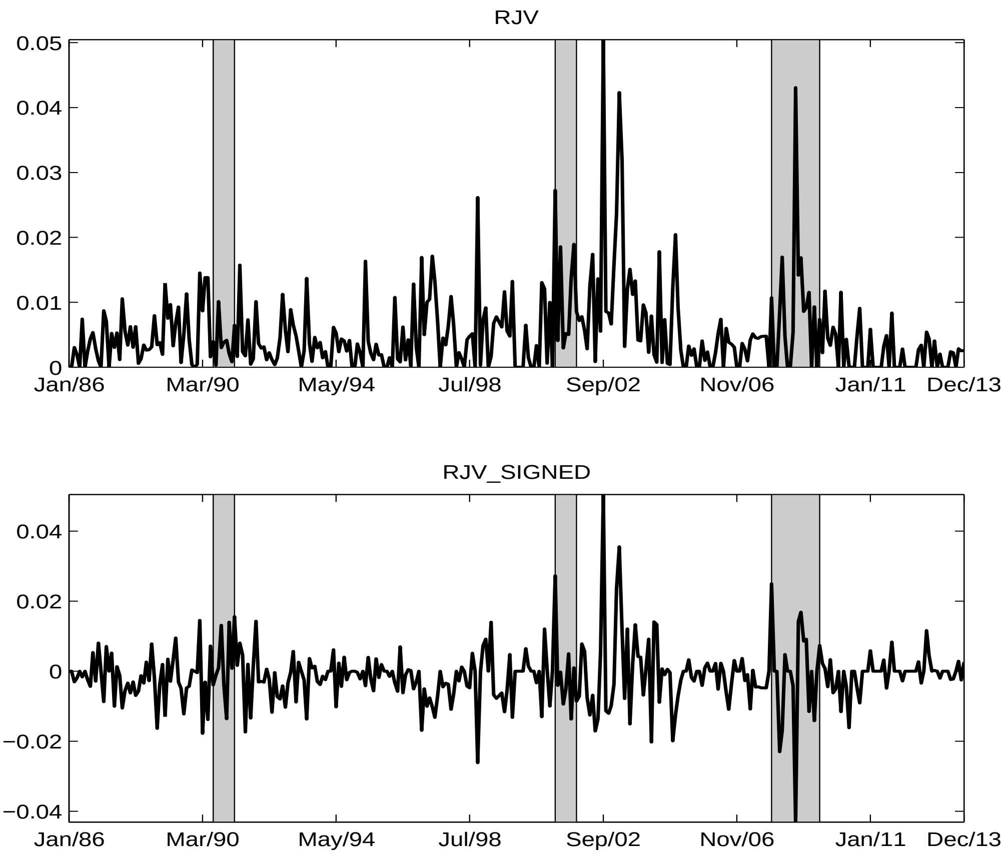

Figure 1: Realized Jump Volatility and Realized Signed Jump Volatility

RJV is the realized jump volatility and RJV_SIGNED is the realized signed jump volatility. The monthly data spans the January 1986 to December 2013 period. Shaded areas indicate business recessions dated by the National Bureau of Economic Research.

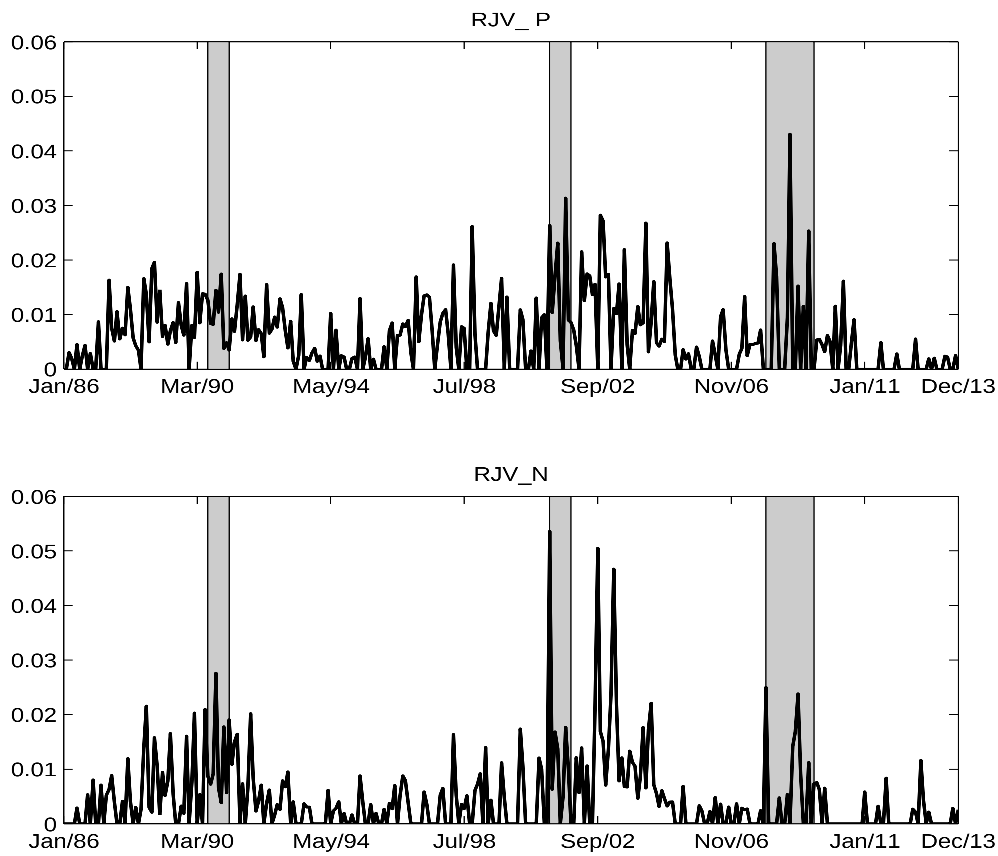

Figure 2: Realized Negative and Positive Jump Volatilities

RJV_P is the realized jump volatility due to positive jumps and RJV_N is the realized jump volatility due to negative jumps. The monthly data spans the January 1986 to December 2013 period. Shaded areas indicate business recessions dated by the National Bureau of Economic Research.

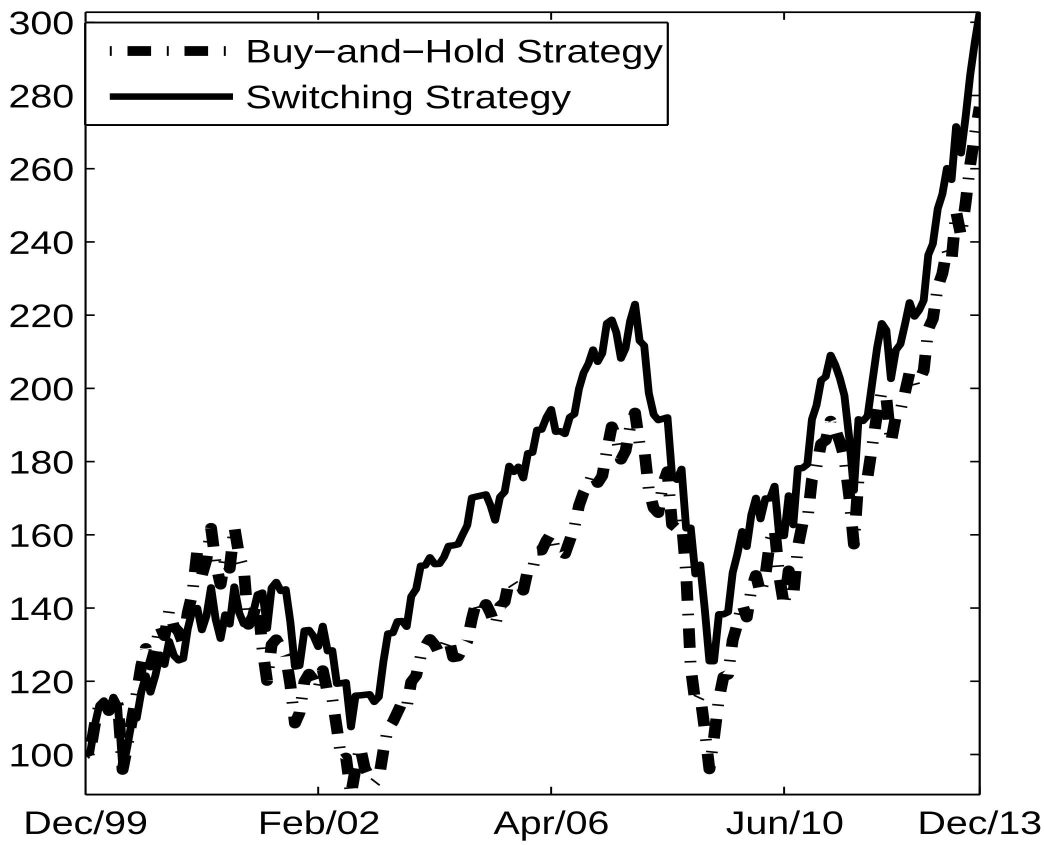

Figure 3: Performance of Switching Strategy

This figure compares performance of an investment with the initial value of 100 dollar of two strategies: (1) The switching strategy using the realized signed jump volatility (RJV_SIGNED) as the timing indicator and (2) the buying-and-holding market index strategy.

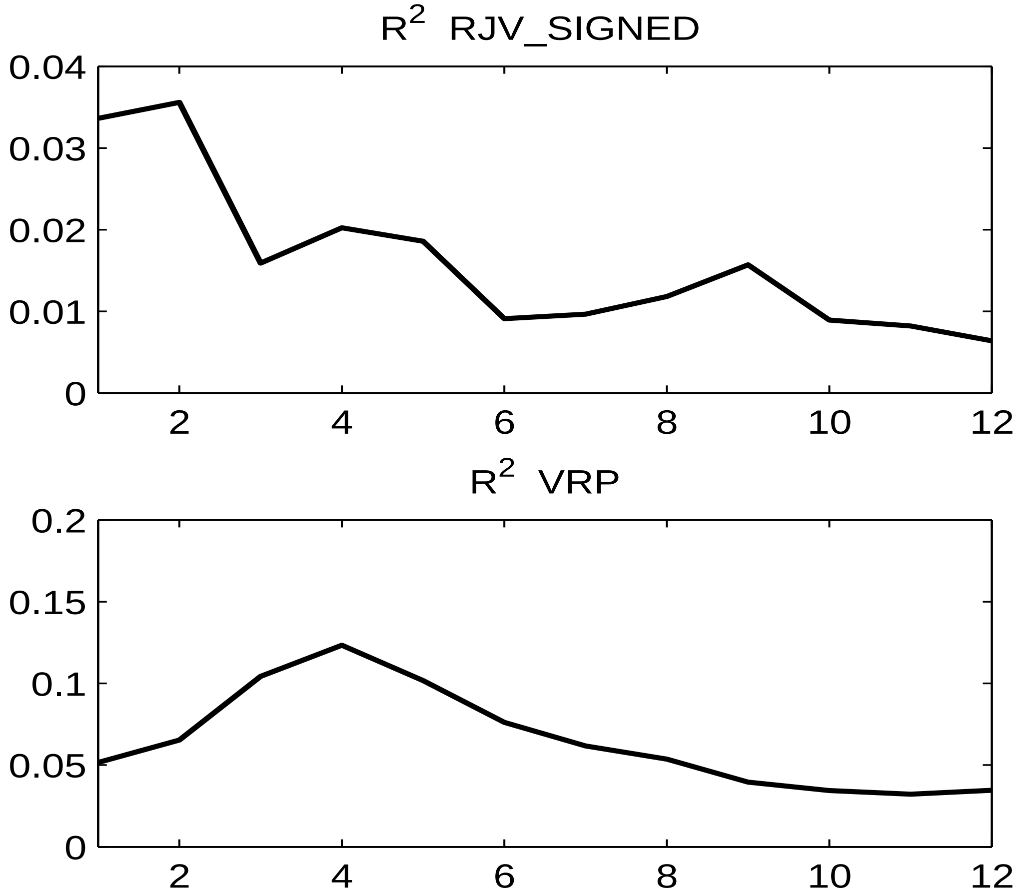

Figure 4: Multi-Month R^2 of Forecasting Returns

This figure reports the R^2 of the return forecasting regressions over different horizons for the realized signed jump volatility (RJV_SIGNED) and variance risk premium (VRP).