Tail Risk and Return Predictability for the Japanese Equity Market*

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Abstract

This paper studies the predictability of the Japanese equity market, focusing on the forecasting power of nonparametric volatility and tail risk measures obtained from options data on the S&P 500 and Nikkei 225 market indices. The Japanese market is notoriously difficult to forecast using standard predictive indicators. We confirm that country-specific regressions for Japan – contrary to existing evidence for other national equity indices – produce insignificant predictability patterns. However, we also find that the U.S. option-implied tail risk measure provides significant forecast power both for the dollar-yen exchange rate and the Japanese excess returns, especially when measured in U.S. dollars. Thus, the dollar-denominated Japanese returns are, in fact, predictable through the identical mechanism as for other equity market indices, suggesting a high degree of global integration for the Japanese financial market.

Keywords: Tail Risk, Variance Risk Premium, Option Markets, Return Predictability.

JEL classification: G12, G13, G15, G17.

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1 Introduction

An extensive literature suggests that a number of economic and financial variables possess forecast power for long-horizon excess returns on the aggregate equity market. The early contributions emphasize predictors such as the ratio of prices to dividends or earnings, see, e.g., Campbell and Shiller (1988a,b), Fama and French (1988), and Hodrick (1992), as well as a variety of interest and yield spread measures, see Campbell (1987), Fama and French (1989), and Keim and Stambaugh (1986), among others. However, subsequently, a number of studies assert that methodological issues, primarily due to the extreme persistence of the predictors and potential model misspecification, severely distort the associated inference procedures. For example, Ang and Bekaert (2007), Welch and Goyal (2008), Boudoukh et al. (2008), and Hjalmarsson (2011) conclude that there is no credible evidence of long-run predictability for the U.S. aggregate market returns. Nonetheless, the topic remains unsettled, and the hypothesis that expected excess returns—the equity risk premium—varies over time, and in particular across the business cycle, remains widely accepted.

To assess the robustness of these findings, various authors explore the forecast power of the same predictors for major international stock markets. As for the U.S., the predictors often generate predictive patterns according to standard inference procedures, although the findings vary and never provide a fully coherent picture across countries. The Japanese equity market has attracted particular attention, as the studies typically fail to produce significant results and, more generally, reveal features that deviate substantially from the usual pattern in other developed countries, see, e.g., Schrimpf (2010), Aono and Iwaisako (2010, 2011, 2013), and Tsuji (2009) for recent evidence.

Meanwhile, over the past decade, a separate set of studies documents significant medium-term predictability for stock returns based on the premium associated with exposure to equity return variation. Specifically, Bollerslev et al. (2009) find that the variance risk premium, obtained as the gap between the option-based risk-neutral and the statistically expected future return variation, predicts the equity risk premium for horizons spanning four to twelve months. Not surprisingly, this finding has also been studied extensively, including for international markets, with authors generally confirming the positive association among the variance and equity risk premiums, albeit with varying degrees of significance depending on the particular equity index and sample period explored. One advantage of the variance risk premium (from a statistical point of view) is that, relative to the extremely persistent regressors used in the long-horizon predictability studies, it is substantially less persistent, generating fewer econometric problems. Nonetheless, as for the macroeconomic and yield-based predictors, the evidence for predictability via the variance risk premium is absent in the Japanese stock market, see, e.g., Londono (2011), Bollerslev et al. (2014), and Ubukata and Watanabe (2014).

Finally, a number of recent studies reveal that the predictability afforded by the variance risk premium stems largely from the left jump tail, as detailed for the U.S. market in Bollerslev et al. (2015). Specifically, Andersen et al. (2015, 2019) document strong predictability associated with the left tail component for both the U.S. and a set of European equity indices, while they also find that the variance risk premium, stripped of the left tail premium, has insignificant predictive power for all indices. These results suggest that the compensation for exposure to abrupt downside movements in the index is at the core of the return predictability.

In this paper, we seek to establish whether the documented lack of forecast power for the variance risk premium in Japan represents yet another fundamental difference vis-a-vis other developed economies, or whether, alternatively, the results may arise from the way equity tail risk is compensated in the Japanese financial markets.

To achieve this goal, we follow Bollerslev and Todorov (2014) and Bollerslev et al. (2015) and construct model-free measures of left tail variation from the option data for the U.S. and Japanese stock market indices. The tail measures are based on extreme value theory, and to the best of our knowledge, have not been constructed before for the Nikkei index. We document that, as for the U.S. stock market, deep out-of-the-money log-put prices written on the Japanese market index decay linearly as function of their log-strikes, consistent with what is implied by regular variation of the left tail of the underlying return distribution. Our measures of tail variation on the U.S. and Japanese markets have similarities and notable differences in their time series behavior. For example, they both increase around the time of the financial crisis in the Fall of 2008, but the Japanese tail measure also reacts strongly to country-specific events such as the Fukushima earthquake. The differences in the time series behavior of the two tail measures manifest themselves in different predictive ability for the Japanese equity risk premium. For Japan, we verify that return predictability is elusive using traditional country-specific predictors: neither the variance risk premium nor the left tail jump risk premium provide significant forecasts for the future Nikkei 225 index returns. On the other hand, the U.S. tail measure shows weak predictability for the Japanese stock market returns, while the results turn highly significant for the corresponding dollar-denominated returns. Thus, from the point of view of a global investor, the predictive results for the Japanese market are similar to these in other leading stock markets.

The remainder of this paper is structured as follows. Section 2 describes our data sources, with an emphasis on the Japanese option data which have not been explored for this type of analysis previously. Section 3 introduces the theoretical framework and details our estimation and implementation procedures. Section 4 presents results for predictive regressions involving the country-specific option and financial market data. In Section 5, we adopt a global perspective, letting the U.S. left tail jump premium serve as predictor for the yen- and dollar-denominated Japanese equity index. Section 6 explores whether equity tail-risk compensation can also help predict future movements in the dollar-yen exchange rate, and Section 7 provides concluding remarks. Additional results and details regarding the empirical implementation are available in a Supplementary Appendix.

2 Data

We rely on data for the primary equity market indices in the U.S. and Japan from January 1996 to June 2018. We proxy the market portfolio in Japan with the Nikkei 225 Total Return Index (Nikkei 225) provided by Nikkei inc., capturing the performance of the Nikkei Stock Average. It includes changes in the index level and reinvestment of dividend income from its 225 constituent stocks listed on the first section of the Tokyo Stock Exchange.[1] Similarly, we use the S&P 500 Total Return Index (S&P 500) to account for dividends.[2] The index values, sampled at the end of each month in Japan, are expressed both in local currency and U.S. dollars. We obtain the local excess returns by subtracting the three-month Treasury bill rate in the U.S. and the unsecured overnight call rate in Japan from the respective local (continuously compounded) market return. The U.S. dollar-denominated Nikkei 225 excess returns equal the yen Nikkei 225 market returns plus the log U.S. dollar-Japanese yen exchange rate return minus the U.S. risk-free rate.

[1] The TOPIX Total Return Index (cum dividends) is available from the Tokyo Stock Exchange (TSE). This value-weighted index is based on all domestic common stocks in the first section of the TSE. Figures A.1–A.3 of the Supplementary Appendix document that our results are qualitatively identical for the TOPIX Total Return Index.

[2] In calculating the total return index for the S&P 500, dividends paid by the individual companies are invested in the entire index, not just in the stock paying the dividend.

Descriptive statistics for the monthly return series from February 1996 to July 2017 (258 months)—corresponding to the period over which we produce forecasts regarding future returns—are provided in Table 1.[3] The mean monthly dollar- and yen-denominated excess returns for the Japanese market are −0.10% and 0.08%, with monthly values ranging from −19.6% to 16.5% and −27.3% to 12.2%, respectively. These figures are qualitatively similar for the U.S. index, except for the markedly better average return of 0.50%. The monthly dollar-yen returns have relatively small standard deviations, but the kurtosis of 5.52 is comparable to those for the market excess returns. The estimated first-order autocorrelation of the monthly returns ranges from 0.01 for the dollar-yen rate to 0.12 for the dollar denominated Nikkei 225 index. In Panel B, the sample cross-correlations of the local equity-index returns versus the dollar-yen exchange rate returns are negative but, not surprisingly, positive for the dollar-denominated Nikkei 225 index.

Next, we describe our Japanese option data in some detail, as they typically have not been available for prior empirical studies. The Nikkei 225 index options are obtained from Nikkei NEEDS Financial Quest 2.0, which provides closing bid and ask quotes as well as transaction prices for options traded on the Osaka Securities Exchange. The Nikkei 225 options are European style, and each contract trades until the business day preceding the second Friday of the expiration month (or if the second Friday is a non-business day, the preceding business day). The final settlement price, known in Japan as the special quotation or SQ, is calculated based on the total opening prices of each component stock of Nikkei 225 on the business day following the last trading day. We remove contracts with zero bid or ask quotes, and we compute the daily mid-quote as the simple average of the bid and ask quote for each available option contract.[4]

Table 2 summarizes the main features of our Nikkei 225 out-of-the-money (OTM) option data covering January 2006 to June 2017. We do not use data prior to 2006 due to the sparcity of deep OTM options needed to estimate the implied jump risk measures. In Panel A, the OTM options are sorted by tenor in calendar days. The average percentage bid-ask spread is the simple average of $100 \times (ask - bid)/ask$. The average daily number of put options is about 50 versus 36 call options,

[3]The last observation exploited to generate return predictions is June 2017, while returns up to the end of June 2018 are used to assess forecast performance over one to twelve month horizons.

[4]The Osaka Securities Exchange introduced options with expiry for each of the nearest four weeks beginning May 25, 2015. Without access to weekly options in Japan over our sample period, we also restrict ourselves to regular monthly S&P 500 options for the U.S.

and the average bid-ask spread for puts ranges from around 13% to 17%, lower than the call range of 15% to 19%. The available contracts are fairly evenly distributed across tenors from a few weeks till three months. The average Black-Scholes implied volatility (BSIV) of the put contracts exceeds those for the calls by a substantial margin at about 34% versus 23%.

In Panel B, the near- and next-term OTM options are sorted by moneyness, defined as the ratio of the strike over forward price. These two option categories are used in the calculation of model-free implied volatility measures at the end of each month. The near-term includes the shortest maturity option each trading day, excluding those with less than eight days to expiration. The average number of near- and next-term OTM options are around 29 and 37 per trading day, respectively. The bid-ask spreads for the deep OTM options are higher than those for at-the-money (ATM) options. The usual volatility skew in equity-index options is also present in Japan, as the BSIV for the deep OTM put options, in particular, are much higher than for the ATM options.

Panel C provides information on the deep OTM put and call options available per week using the moneyness definition commensurate with the construction of our nonparametric tail measures. The OTM metric is now defined as the log-moneyness normalized by the ATM BSIV. The figures refer to options with tenor between eight and forty-four days only, and we report on the initial part of the sample separately to convey the growth in liquidity over time. As seen from the table, even early in our sample, we have a considerable number of deep OTM options (volatility-standardized log-moneyness below -2.5 for puts, above 1.5 for calls) available. Overall, this Nikkei OTM option sample provides a good basis for the computation of the option-based jump risk measures introduced in the following section.

3 Nonparametric Option-Based Risk Measures

3.1 Decomposing Variance Risk Premium

The generic asset price S_t is defined on a filtered probability space $(\Omega, \mathcal{F}, \mathbb{P})$, with $(\mathcal{F}_t)_{t\geq 0}$ denoting the associated filtration. We assume S_t follows a stochastic exponential of a general jump-diffusion,

$$dS_t/S_{t-} \;=\; a_t\,dt \;+\; \sigma_t\,dW_t \;+\; \int_{\mathbb{R}} (e^x - 1)\,\tilde{\mu}^{\mathbb{P}}(dx, dt), \tag{1}$$

where the drift and diffusive processes, a_t and σ_t , are assumed to have càdlàg paths, but otherwise are left unspecified, W_t is a standard Brownian motion, x indicates the jump size of the log-price, $\tilde{\mu}^{\mathbb{P}}(dx, dt) \equiv \mu(dx, dt) - \nu_t^{\mathbb{P}}(dx)dt$ is a martingale measure under the actual probability measure, $\mathbb{P}$, where $\mu(dx, dt)$ counts the jumps in S, and $\nu_t^{\mathbb{P}}(dx)$ denotes the jump compensator, i.e., the (predictable) jump intensity process under $\mathbb{P}$. The return variation of the log-price process over t to $t + \tau$ is measured by the quadratic variation,

$$\mathcal{QV}_{t,t+\tau} = \int_t^{t+\tau} \sigma_s^2 \, ds + \int_t^{t+\tau} \int_{\mathbb{R}} x^2 \, \mu(dx, ds). \tag{2}$$

We assume the existence of a risk-neutral probability measure, $\mathbb{Q}$, under which the cum-dividend discounted asset price is a local martingale.[5] The $\mathbb{P} - \mathbb{Q}$ wedge is due to compensation for risk, i.e., a risk premium. In particular, the variance risk premium, normalized by the horizon, $VRP_{t,\tau}$, is given by the gap between the conditional expectations of $\mathcal{QV}_{t,t+\tau}$ under the risk-neutral and objective measures, $\mathbb{Q}$ and $\mathbb{P}$,

$$VRP_{t,\tau} \equiv \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{QV}_{t,t+\tau}] - \mathbb{E}_t^{\mathbb{P}}[\mathcal{QV}_{t,t+\tau}]\Big), \tag{3}$$

which represents compensation for the risk associated with fluctuations in the return variation.[6]

The VRP provides compensation for two distinct types of risks: time-varying volatility and jumps. Letting $\mathcal{CV}_{t,t+\tau} = \int_t^{t+\tau} \sigma_s^2 ds$ be the continuous variation, and $\mathcal{JV}_{t,t+\tau}^{\mathbb{P}} = \int_t^{t+\tau} \int_{\mathbb{R}} x^2 \nu_s^{\mathbb{P}}(dx) ds$ and $\mathcal{JV}_{t,t+\tau}^{\mathbb{Q}} = \int_t^{t+\tau} \int_{\mathbb{R}} x^2 \nu_s^{\mathbb{Q}}(dx) ds$ denote the predictable jump variation under $\mathbb{P}$ and $\mathbb{Q}$, respec-

[5] The existence of $\mathbb{Q}$ is guaranteed by no-arbitrage under standard regularity conditions, see, e.g., Duffie (2001).

[6] The variance risk premium is usually defined, $VRP_{t,\tau} \equiv \mathbb{E}_t^{\mathbb{P}}[\mathcal{QV}_{t,t+\tau}] - \mathbb{E}_t^{\mathbb{Q}}[\mathcal{QV}_{t,t+\tau}]$, whereas the return predictability literature often uses the expression (3), e.g., Londono (2011) and Bollerslev et al. (2014), to obtain an (average) positive premium. Consumption-based asset pricing models incorporating time-varying economic uncertainty imply a positive relationship between the equity risk premium and variance risk premium, which may serve as a gauge of investor risk aversion; see Bollerslev et al. (2009, 2011) and Drechsler and Yaron (2011).

tively, we may decompose the VRP as,

$$
\begin{aligned}
VRP_{t,\tau} &= \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{CV}_{t,t+\tau}] - \mathbb{E}_t^{\mathbb{P}}[\mathcal{CV}_{t,t+\tau}]\Big) + \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{Q}}] - \mathbb{E}_t^{\mathbb{P}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{P}}]\Big) \\
&= \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{CV}_{t,t+\tau}] - \mathbb{E}_t^{\mathbb{P}}[\mathcal{CV}_{t,t+\tau}]\Big) + \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{P}}] - \mathbb{E}_t^{\mathbb{P}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{P}}]\Big) \\
&+ \frac{1}{\tau}\Big(\mathbb{E}_t^{\mathbb{Q}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{Q}}] - \mathbb{E}_t^{\mathbb{Q}}[\mathcal{JV}_{t,t+\tau}^{\mathbb{P}}]\Big). \qquad (4)
\end{aligned}
$$

The terms in the middle line of equation (4) reflect compensation for the risk associated with variation in the diffusive volatility and jump intensity risk. They may be viewed as premiums incurred for hedging against changes in the investment opportunity set for the aggregate market portfolio. By contrast, the last term captures the wedge between the $\mathbb{Q}$ and $\mathbb{P}$ jump variation under the risk-neutral measure. It signifies compensation for the possibility that jumps may occur, as distinct from the compensation for temporal variation in the jump intensity.[7] Bollerslev et al. (2015) and Andersen et al. (2015, 2019) find that a large portion of the predictability of the U.S. aggregate stock returns might be attributed to the compensation for this jump tail risk component. We now introduce our jump tail risk measurement procedures for the U.S. and Japanese markets.

3.2 Estimating Implied and Expected Realized Variance and Jump Tail Risk

We start with reviewing the essentially model-free estimation procedure for the variance risk premium and its jump tail risk component. We obtain the VRP as the difference between a model-free option-implied variance and an expected realized variance. The former approximates the risk-neutral expectation of the quadratic variation for the market index over a fixed maturity using the option prices for the corresponding tenor. As shown by Carr and Madan (1998), Demeterfi et al. (1999) and Britten-Jones and Neuberger (2000), we have,

$$
\frac{1}{\tau}\,\mathbb{E}_t^{\mathbb{Q}}[\mathcal{QV}_{t,t+\tau}] \;\approx\; \frac{2\,e^{r_t\tau}}{\tau}\left(\int_0^{F_{t,\tau}} \frac{P_{t,\tau}(K)}{K^2}\,dK + \int_{F_{t,\tau}}^{\infty} \frac{C_{t,\tau}(K)}{K^2}\,dK\right), \qquad (5)
$$

[7]See section 5 in Bollerslev and Todorov (2011) and section 2.2 in Bollerslev et al. (2015) for detailed discussion.

where r_t is the risk-free rate, $P_{t,\tau}(K)$ and $C_{t,\tau}(K)$ are the European put and call option prices with strike K, $F_{t,\tau}$ is the forward price, all at time t and with maturity date $t+\tau$.[8]

This representation constitutes the basis for well-known model-free market volatility indices, including the VIX. We approximate the integral on the right-hand side of equation (5) using a Riemann sum and option prices on an equidistant grid of $1,001$ strikes covering a range of three times the standard deviation around the log forward price. Options on this grid are in turn approximated from the available ones using cubic spline interpolation in the BSIV space. Outside this range —beyond the smallest and highest available strikes—the BSIV level is assumed flat. Finally, thirty (calendar) day implied measures are calculated by linear interpolation across the two nearest maturities, excluding maturities below eight days. This approach is known to work well for S&P 500 index options, see Carr and Wu (2009).[9] Panel B of Table 2 in Section 2 characterizes the basic features of the Japanese OTM option sample available for estimation.

For the $\mathbb{P}$-conditional expectation of the quadratic variation, $E_t^{\mathbb{P}}[\mathcal{QV}_{t,t+\tau}]$, we use a realized variance forecast based on a standard time-series model. First popularized by Andersen and Bollerslev (1998), Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002), the realized variance, defined as the sum of the squared intraday returns over the interval, provides an accurate estimate of the quadratic variation in the absence of microstructure noise induced by frictions such as bid-ask bounce and non-synchronous trading. To mitigate microstructure effects, we rely on daily realized variances obtained from five-minute returns generated by the Oxford-Man Institute Realized Library. Next, we estimate the heterogeneous autoregressive (HAR) model of Corsi (2009), using the past 900 daily realized variances. It is a simple approximate long-memory model for the daily realized volatility, that uses the one-day, five-day (one week) and twenty-two trading day (one month) lagged realized variance as joint (reduced-form) predictors. Given the estimated parameters, the

[8]Equation (5) is subject to a minor approximation error. The right-hand side of equation (5) equals $\frac{1}{\tau}\int_t^{t+\tau}\mathbb{E}_t^{\mathbb{Q}}(\sigma_s^2)ds + \frac{2}{\tau}\int_t^{t+\tau}(e^x-1-x)\mathbb{E}_t^{\mathbb{Q}}(\nu_s^{\mathbb{Q}}(dx))$ which, up to a third order term (in an expansion around zero), equals $(1/\tau)\mathbb{E}_t^{\mathbb{Q}}[\mathcal{QV}_{t,t+\tau}]$. However, this discrepancy is immaterial in the context of our predictive regressions (as what matters for them is the variation in time of $\nu_t^{\mathbb{Q}}(dx)$ and the latter typically is the same for jumps of different size) and, henceforth, we ignore it.

[9]Given the tail calculations that we implement later based on equation (10) below, we can alternatively utilize those in the tail approximation for the integral in equation (5). We do not do this here for two reasons. One is to be consistent with existing work on variance risk premium. The second is that the tail approximation has only a limited impact on the overall risk-neutral variation given the strike range of the available options.

direct one-period-ahead forecast for the realized variance is used as our estimate of $E_t^{\mathbb{P}}[\mathcal{QV}_{t,t+\tau}]$.

A largely non-parametric option-based measure for the varying jump tail component of the variance risk premium, represented by the third term in equation (4), is put forth by Bollerslev et al. (2015). Define the left and right (predictable) risk-neutral jump variation over the interval by,

$$LJV_{t,\tau}^{\mathbb{Q}} = \int_t^{t+\tau}\int_{x<-k_t} x^2\nu_s^{\mathbb{Q}}(dx)ds, \qquad RJV_{t,\tau}^{\mathbb{Q}} = \int_t^{t+\tau}\int_{x>k_t} x^2\nu_s^{\mathbb{Q}}(dx)ds, \tag{6}$$

where $k_t > 0$ is a time-varying cutoff for the log-jump size. We denote $LJV_{t,\tau}^{\mathbb{P}}$ and $RJV_{t,\tau}^{\mathbb{P}}$ as the corresponding left and right predictable jump tail variation measures under $\mathbb{P}$. The left and right jump tail premium are then formally defined as,

$$LJP_{t,\tau} = \frac{1}{\tau}\left(\mathbb{E}_t^{\mathbb{Q}}[LJV_{t,\tau}^{\mathbb{Q}}] - \mathbb{E}_t^{\mathbb{P}}[LJV_{t,\tau}^{\mathbb{P}}]\right), \quad RJP = \frac{1}{\tau}\left(\mathbb{E}_t^{\mathbb{Q}}[RJV_{t,\tau}^{\mathbb{Q}}] - \mathbb{E}_t^{\mathbb{P}}[RJV_{t,\tau}^{\mathbb{P}}]\right). \tag{7}$$

LJP and RJP are components of VRP, and they are naturally connected with the equity risk premium, as they reflect compensation for price jump tail risk, which is an integral component of the equity return risk. As we show below, we can construct proxy measures for $\mathbb{E}_t^{\mathbb{Q}}[LJV_{t,\tau}^{\mathbb{Q}}]$ and $\mathbb{E}_t^{\mathbb{Q}}[RJV_{t,\tau}^{\mathbb{Q}}]$ from the option data. On the other hand, constructing measures from the return data for $\mathbb{E}_t^{\mathbb{P}}[LJV_{t,\tau}^{\mathbb{P}}]$ and $\mathbb{E}_t^{\mathbb{P}}[RJV_{t,\tau}^{\mathbb{P}}]$ is challenging, because of the few tail events we observe in a typical sample, including the one we use here. Hence, we exploit several empirical facts. First, the realized jump tail risk is close to symmetric. Indeed, the null hypothesis, $LJV_{t,\tau}^{\mathbb{P}} = RJV_{t,\tau}^{\mathbb{P}}$, is not rejected at the monthly frequency using truncated realized left and right return variation measures calculated from high-frequency index return data. This is consistent with prior findings, e.g., Bollerslev and Todorov (2011), and with daily returns, see Schwert (1990). Therefore,

$$LJP_{t,\tau} - RJP_{t,\tau} \approx \frac{1}{\tau}\left(\mathbb{E}_t^{\mathbb{Q}}[LJV_{t,\tau}^{\mathbb{Q}}] - \mathbb{E}_t^{\mathbb{Q}}[RJV_{t,\tau}^{\mathbb{Q}}]\right), \tag{8}$$

which involves only $\mathbb{Q}$ expectations and reflects the pricing of negative tail events. Next, we find that the left jump tail variation is an order of magnitude larger than the right one for our equity indices. Therefore, we can approximate the jump tail risk premium by the $\mathbb{Q}$ expectation of the left jump variation,

$$LJP_{t,\tau} - RJP_{t,\tau} \;\approx\; \frac{1}{\tau}\,\mathbb{E}_t^{\mathbb{Q}}[\,LJV_{t,\tau}^{\mathbb{Q}}\,]. \tag{9}$$

Our estimation procedure for $LJV_{t,\tau}^{\mathbb{Q}}$ is based on a general specification for the jump intensity processes under $\mathbb{Q}$, following Bollerslev and Todorov (2014),[10]

$$\nu_t^{\mathbb{Q}}(dx) \;=\; \left(\phi_t^{+} \times e^{-\alpha_t^{+} x}\, 1_{\{x>0\}} \;+\; \phi_t^{-} \times e^{-\alpha_t^{-}|x|}\, 1_{\{x<0\}}\right) dx, \tag{10}$$

where $\alpha_t^{\pm}$ and $\phi_t^{\pm}$ represent the time-varying shape and level shift parameters of the right and left jump tails, respectively. This model allows both the level and shape of the jump intensity function to vary over time, providing significantly more flexibility than existing parametric option pricing models for which only the level, but not the shape, of the jump intensity may vary over time.

Given specification (10) and following Bollerslev and Todorov (2014), we obtain the following approximation for the OTM put option prices,

$$O_{t,\tau}(k) \;\approx\; \tau\, e^{-r_t \tau}\, F_{t,\tau}\; \phi_t^{-}\, \frac{e^{k(1+\alpha_t^{-})}}{\alpha_t^{-}(\alpha_t^{-}+1)}, \qquad k<0, \tag{11}$$

where $O_{t,\tau}(k)$ denotes the OTM option price corresponding to log-moneyness k. This approximation is built using both the specification for the jump intensity in equation (10) and the fact that for short-dated options, the OTM option price with log-moneyness away from zero is dominated by the jumps in the underlying price, see, e.g., Bollerslev and Todorov (2011, 2014).

Using the approximation (11), the estimates of α_t^{-} and ϕ_t^{-} are generated as the solutions to the following minimization problem,

$$\begin{aligned}
\hat{\alpha}_t^{-} \;&=\; \arg\min_{\alpha^{-}} \frac{1}{N_t^{-}} \sum_{i=2}^{N_t^{-}} \left| \log\!\left(\frac{O_{t,\tau}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})}\right)(k_{t,i}-k_{t,i-1})^{-1} - (1-(-\alpha^{-})) \right|, \\
\hat{\phi}_t^{-} \;&=\; \arg\min_{\phi^{-}} \frac{1}{N_t^{-}} \sum_{i=2}^{N_t^{-}} \left| \log\!\left(\frac{e^{r_t\tau}O_{t,\tau}(k_{t,i})}{\tau F_{t,\tau}}\right) - (1+\hat{\alpha}_t^{-})k_{t,i} + \log(\hat{\alpha}_t^{-}+1) + \log(\hat{\alpha}_t^{-}) - \log(\phi^{-}) \right|,
\end{aligned} \tag{12}$$

where N_t^{-} is the total number of puts used in the estimation with $0 < -k_{t,i} < \cdots < -k_{t,N_t^{-}}$ for

[10]In fact, we only need the specification in (10) for the "big" negative jumps as our interest is in the left jump tail.

i-th log-moneyness $k_{t,i}$. Intuitively, the tail shape parameter is inferred from the tail decay of the log-price of puts. Given an estimate for it, the jump intensity parameter is then estimated from the level of the deep OTM put prices.

For short-dated options, we may ignore the time variation in the tail parameters until the option expiration and approximate them by a constant. Following this strategy, and substituting the estimated parameters for the jump intensity process into the left predictable jump variation, we obtain our proxy for the expected left jump tail variation under $\mathbb{Q}$,

$$\mathbb{E}_t^{\mathbb{Q}}[\, LJV_{t,\tau}^{\mathbb{Q}}\,] \;\approx\; \tau\, \phi_t^- \; e^{-\alpha_t^- |k_t|}\,(\, \alpha_t^- k_t(\alpha_t^- k_t + 2) \,+\, 2\,)\,/\,(\alpha_t^-)^3. \tag{13}$$

Similar to Bollerslev et al. (2015), we set τ equal to thirty calendar days, or one month, and the time-varying cutoff k_t is fixed at seven times the normalized ATM BSIV at time t in our calculation of the expected U.S and Japanese left jump variation.

3.3 Empirical Implementation

Theoretically, the estimators of α_t^- (α_t^+) and ϕ_t^- (ϕ_t^+) require us to use deep OTM put (call) options at short tenor to mitigate the effect of the diffusive price component. However, for our sample period very short-dated options were not available for the Japanese market, and those that were quoted were fairly illiquid. Thus, to avoid the impact of market microstructure effects, we use options with maturities between 8 and 44 calendar days. Moreover, if the monotonicity condition that the OTM put (call) option prices are increasing (decreasing) in strike price is violated, we retain the option with the highest volume and, subsequently, the option closest to the ATM one. To obtain a sufficient number of Japanese options for estimation of α_t^- and ϕ_t^-, as summarized in Panel C of Table 2, we rely on put options with log-moneyness less than -2.0 and -2.5 times the normalized ATM BSIV before and after December 2008, respectively, while we adopt the value of -2.5 over the full January 1996 to June 2017 sample for the put options on the S&P 500 index.

To mitigate the impact of noise, we assume α_t^- only changes at a weekly frequency, while we allow ϕ_t^- to vary each trading day.[11] We then compute weekly $LJV^{\mathbb{Q}}$ measures by averaging the daily measures and obtain the monthly jump variation by averaging the weekly measures within the

[11] Most existing parametric models for the jump distribution impose time-invariant jump distribution corresponding to a constant α_t^-.

month. To illustrate how the left tail parameter α_t^- is estimated using equation (12), Figure 1 plots the slope estimates of the OTM put decay, given by $\log(O_{t,\tau}(k_{t,i})/O_{t,\tau}(k_{t,i-1}))/(k_{t,i}-k_{t,i-1})$, versus the log-moneyness $k_{t,i}$ for weeks reflecting diverse market conditions. The panels are obtained by pooling the Nikkei 225 OTM options over an early week in our sample, January 18 to 24, 2006 (upper left), from a period when the LJV is relatively low prior to the 2008-2009 financial crisis, December 8 to 14, 2007 (upper right), from the tumultuous period during the crisis, November 22 to 28, 2008 (Panel C), December 10 to 16, 2008 (Panel D), from the turbulent week, March 25 to 31, 2011, following the Japanese earthquake (Panel E), and from more recent weeks, August 16 to 22, 2014 (Panel F), September 3 to 9, 2015 (lower left) and June 10 to 16, 2017 (lower right), respectively. The flat dotted line represents the estimates $1 + \hat{\alpha}^-$ in (12). The fact that we do not identify any significant patterns in the configuration of the data points across the panels support the use of a weekly α_t^- measure. That is, in the tail representation (10), $\log(O_{t,\tau}(k_{t,i})/O_{t,\tau}(k_{t,i-1}))/(k_{t,i}-k_{t,i-1})$ should fluctuate randomly around its true value of $1+\alpha_t^-$, and this is largely confirmed by the panels in Figure 1. Indeed, the OTM put decay displays only limited dependence on the log-moneyness, and this dependence is more notable for strikes close to the money, for which the presence of the diffusion in the stock price dynamics renders the decay slightly stronger. The latter feature is consistent with theory, and it is accommodated by our measurement procedure.[12]

On the other hand, the distinctly different values of the left jump tail parameter α_t^- across the panels suggest significant time variation over the sample period. Specifically, at times, we observe an unusually slow rate of decay for the log option put prices as we consider increasingly OTM contracts (low values of α_t^-), implying a fat left tail of the risk-neutral density. This is particularly true for the weeks in November and December 2008, during the financial crisis, the week of March 25 to 31, 2011, following the earthquake disaster, and September 3 to 9, 2015, right after large U.S. stock market losses in August ascribed to anxiety over interest rate hikes, tumbling oil prices and turbulence in the Chinese markets. In comparison, the tail index is much higher for the other panels in Figure 1, representing more tranquil market conditions. For further assessment of the tail measures, Figure 2 depicts the estimated monthly Japanese left jump tail index series along with the one for the U.S., which is derived from the more liquid S&P 500 options. The Japanese series

[12]Recall from equation (11) that our estimation is based on approximating the short-dated OTM put price by ignoring the diffusion component in the stock price dynamics.

starts out lower than in the U.S. during the tranquil markets of 2006-2007, but effectively converges to the U.S. index as the financial crisis approaches. In the aftermath of the crisis, the series remain fairly coherent, but there is also strong evidence of spikes in the Japanese tail index that reflect more local concerns associated with the Fukushima earthquake and shifts in the perception of the economic policy under Prime minister Abe in Japan. Both the coherence and readily interpretable divergencies among the series suggest that they are economically meaningful.

The jump tail indices have a direct impact on the corresponding variance and tail jump risk variation measures. Table 3 provides descriptive statistics and sample cross-correlations for the monthly VRP series and their tail jump risk components for the two countries in percentage form, while Figure 3 displays the corresponding series in annualized percentage units. The samples comprise January 1996 to June 2017 for LJV-US, January 2000 to June 2017 for VRP-US, and January 2006 to June 2017 for Japan. The contemporaneous correlations are estimated for January 2006 to June 2017. All VRPs have a significantly positive mean, indicating that the risk-neutral expectation of the future return variation systematically exceeds the actual realization. Table 3 and Figure 3 also indicate significant time variation of the jump risk component. In particular, there are clearly discernible peaks associated with specific events, including those around the 2008–2009 financial crisis, the U.S. Flash Crash in May 2011, and the worldwide stock market decline in August 2011. The Japanese jump variation measures are also elevated during the period of Chinese market turbulence starting in the middle of 2015 and culminating in early 2016.[13] We note that the summary statistics of LJV-JPN are qualitatively similar to those for LJV-US but, consistent with the tail index estimates in Figure 2, there are unique spikes in LJV-JPN around the earthquake disaster in March 2011 and the period of uncertainty associated with the implementation of Abenomics in June 2013. The LJV-US and LJV-JPN are moderately persistent, with first-order monthly autocorrelation coefficients of 0.68 and 0.60. From Panel B of Table 3, the sample correlation between VRP and LJV is 0.03 for U.S. and 0.22 for Japan, indicating that the jump tail risk component may display a different dynamic from the overall VRP. In contrast, LJV-JPN and LJV-US are reasonably coherent, yet not tightly linked, with a sample correlation of 0.49.

[13]The idea that Chinese market instability may have global effects is fairly recent, but reflects the importance of the country in international trade. For example, at the October 2015 International Monetary Fund (IMF) annual meeting in Peru, China's slump dominated discussions with participants asking if China's economic downturn would trigger a new financial crisis; see "China is not collapsing," by Anatole Kaletsky, *Project Syndicate*, October 12, 2015.

4 Country-Specific Stock Return Predictability

Our main focus here is the predictability of excess returns on the Japanese market portfolio, and how the evidence contrasts to that for the U.S. The Japanese market is notoriously difficult to forecast using predictive signals or indicators, that are successful for other national market indices, see, e.g., Campbell and Hamao (1992), Tsuji (2009), Schrimpf (2010), Aono and Iwaisako (2010, 2011, 2013), Li and Yu (2012), and Rapach et al. (2013). Recent studies further confirm that the Japanese VRP is an insignificant predictor for the local market return, see Londono (2011), Bollerslev et al. (2014), and Ubukata and Watanabe (2014), while the market returns in the U.S. and most developed countries in Europe are predictable based on the respective VRPs, see Bollerslev et al. (2009), Drechsler and Yaron (2011), Londono (2011), Du and Kapadia (2013), Bekaert and Hoerova (2014), and Bollerslev et al. (2014), among others.[14]

Meanwhile, recent studies indicate that inclusion of the diffusive and jump risk components of the VRP as separate predictors yields significantly improved forecast power for the aggregate equity market, e,.g., Bollerslev et al. (2015) and Andersen et al. (2015, 2019). Consequently, in this section, we explore country-specific predictive regressions based on the variance risk premium and their jump risk component for both the U.S and Japan.

In line with the literature, we rely on standard monthly predictive return regressions,

$$\frac{1}{h} ER^j_{t,t+h} = \beta_0(h) + \beta_1(h) V^j_t + u^j_{t,t+h}, \quad t = 1, \ldots, T^j, \tag{14}$$

where, henceforth, t refers to the month and $ER^j_{t,t+h}$ denotes $h = 1$ (one month) to $h = 12$ (one year) excess returns for country j = U.S. and JPN, respectively, and for the error term in the regression we assume

$$\mathbb{E}_t(u^j_{t,t+h}) = 0, \tag{15}$$

i.e., that it is a martingale difference sequence. V^j_t in the predictive regression refers to one or more explanatory variables, including the VRP and its diffusive and jump risk components. For statistical inference on the slope coefficient $\beta_1(h)$ in the overlapping multi-period return regression, we rely on regular heteroskedasticity and autocorrelation robust (HAR) Newey and West (1987)

[14] Tables A.1 and A.2 of the Supplementary Appendix provide a summary of the findings from this literature.

t-statistic with a lag length equal to $2h$ (to account for the overlap), consistent with the approach of Bollerslev et al. (2015). However, for robustness, we also compute two alternative sets of critical values for existence of return predictability, i.e., the slope coefficient $\beta_1(h) \neq 0$. These procedures stem from Lazarus et al. (2018, hereafter LLSW), which improve on the standard Newey and West (NW) approach in a wide set of circumstances. The first robust test employs the NW estimator with a lag length of $\lceil 1.3T^{1/2} \rceil$ along with nonstandard fixed-b critical values. The second exploits the Equal-Weighted Cosine (EWC) estimator of the long-run variance with a free parameter rule of $\lfloor 0.4T^{2/3} \rfloor$, which corresponds to the degrees of freedom of the HAR fixed-b t-test. Below, the three statistics used to assess the significance of the slope coefficient are denoted t(NW), b(LLSW) and t(LLSW), respectively.

4.1 The Left Tail Variation as Predictor

Table 4 reports results from univariate regressions based on the left jump tail variation LJV, a proxy for the left jump risk component of VRP, over samples covering January 1996 – June 2017 for the U.S. and January 2006 – June 2017 for Japan. The superscripts a, b and c for the three HAR test statistics t(NW), b(LLSW) and t(LLSW) indicate significance levels 1%, 5%, and 10%, respectively. For predictability of the S&P 500 returns in Panel A of Table 4, LJV-US is significantly positive over forecasting horizons ranging from five to twelve months, consistent with the findings in Bollerslev et al. (2015) and Andersen et al. (2019). It indicates that higher (lower) compensation for U.S. jump tail risks predicts higher (lower) future U.S. market excess returns. The top and bottom left panels of Figure 4 depict the associated t(NW) statistics and adjusted R^2 over the full sample, January 1996 – June 2017 (solid lines) and for January 2006 – June 2017 (dashed lines) corresponding to our Japanese sample. The LJV-US statistic remains significant for the subsample regressions and the adjusted R^2's generally increase with the return horizons, ultimately attaining about 12%. The right panels in Figure 4 provide evidence regarding the predictability patterns obtained from the corresponding regressions, where the predicted and explanatory variables are winsorized at the 2.5% and 97.5% levels. The winsorization mitigates the impact of both large and small observation values, including abnormal inlier events associated with regional holidays and volatile episodes like the Asian financial crisis, the Russian crisis and LTCM shock, the 9/11 terrorist attacks, the Lehman bankruptcy, and the U.S. Flash Crash. The significance of LJV-US in the winsorized regressions corroborates that the predictive ability of the U.S. jump risk component of the VRP for the aggregate market returns is robust.

Turning to Panel B of Table 4, the estimation results for Japan are clearly different relative to the U.S. For the Nikkei 225 excess returns, the slope coefficients of LJV-JPN are positive, consistent with the results for U.S., but t(NW), b(LLSW) and t(LLSW) all indicate that LJV-JPN is insignificant, even at the 10% level, for all forecast horizons. In addition, the adjusted R^2's are low, attaining a maximum of only 1.56%. Figure 5 plots the associated t(NW) statistics and adjusted R^2 (solid lines) along with those from the corresponding winsorized regressions (dashed lines). The robust regressions provide slightly larger t-values and adjusted R^2's for the longer horizons, but the coefficients remain statistically insignificant. Thus, in line with many prior studies, we find that country-specific regressions for standard predictive indicators fail to generate evidence for return predictability in Japan.

4.2 Variance Risk Premium Components as Predictors

To assess the contribution of the left jump tail risk component to the forecast power of the VRP, we explore multiple predictive regressions in which the regressors consist of the LJV measure and the total variance risk premium stripped of the left jump tail variation, $VRP - LJV$. The latter constitutes the primary component of the VRP, attributable to diffusive or normal-sized price fluctuations as well as positive market jumps. The t(NW) and adjusted R^2 statistics from these country-specific regressions are depicted in Figure 6. The predictability pattern associated with the diffusive and positive jump component of VRP is clearly distinct from that of the negative jump tail risk part. The hump-shaped curve for $VRP - LJV$ slope coefficient, peaking around the quarterly horizon for the S&P 500 excess returns, is qualitatively identical to that for the total VRP previously documented in the literature, such as Bollerslev et al. (2009, 2014). However, this measure is significant only at the 10% level, and the adjusted R^2 at the three to four months horizons for the U.S. only increase by about 1% to 2.5% relative to that from the univariate regression based on LJV-US. Moreover, over the longer horizons, the predictability of the S&P 500 excess returns is entirely attributable to the jump tail risk component, consistent with the result in Bollerslev et al. (2015) and Andersen et al. (2019). By contrast, neither the Japanese diffusive risk component nor the jump risk component have significant forecast power for the market excess returns across our entire range of predictive horizons. We confirm that the corresponding adjusted R^2's are lower than those from simple univariate regressions based solely on the local LJV. In summary, among the predictors examined, the left jump tail risk component of the VRP is the primary measure providing significant forecast power for the U.S. equity-index returns. The lack of a corresponding finding for Japan is noteworthy given the consistent evidence for predictive power of the local LJV component for six separate European equity indices in Andersen et al. (2019).

5 International Linkages in Predictability

Section 4 documents that country-specific regressions for Japan—in contrast to the U.S.—produce insignificant return predictability patterns. Hence, consistent with much prior work, Japan seems to constitute an outlier. This finding motivates an examination of the Japanese risk dynamics from a global perspective, using also foreign or international predictors. This is similar in spirit to earlier studies which explore standard U.S. predictors for the Japanese equity returns, such as the U.S. lagged excess returns, relative short rates, dividend yields and long-short yield spreads, see Bekaert and Hodrick (1992) and Campbell and Hamao (1992), among others.

The adoption of an international asset pricing perspective is inspired by an additional set of observations. First, Table 5 reports the percentage of foreign investors in the total brokerage trading value of the Japanese spot and derivatives markets. This data stems from a survey by the Japan Exchange Group covering trading participants with capital of at least 3 billion yen. It shows that foreigners are accountable for a very large fraction of the trading in Japanese equities and associated derivatives, and the share has increased year by year. Uno and Kamiyama (2009) further conclude that foreigners pursue strict monitoring of management and have a relatively short investment horizon for their positions in the Japanese markets. In contrast, Japanese shareholders rely less on active monitoring and tend to have long-term ownership relations. These facts point toward significant degree of integration of the Japanese financial markets with the rest of the world, and hence are suggestive of similar risk premium dynamics from the point of view of a foreign investor.

Second, global economic shocks and major declines in the U.S. stock index tend to induce a sharp appreciation of the Japanese yen and assert strong downward pressure on the Japanese stock index. Such "risk-off" periods induce foreign investors to seek risk mitigation by buying the yen, and this process may be accentuated by large-scale yen carry trade unwinds by hedge funds.

Consequently, it is quite likely that global tail events may be linked closely to developments in the Japanese equity market.

Third, Bollerslev et al. (2014), Londono (2011), and Gao et al. (2018) document that U.S. or global risk-neutral variation measures generally have predictive power for foreign currency-denominated equity indices and other international assets. This suggests that the U.S. LJV tail and VRP measures may serve as indicators for the (dollar-denominated) Nikkei index, even if Bollerslev et al. (2014) find only weak VRP-based predictability for the yen-denominated Nikkei returns.

5.1 U.S. Left Tail Variation and Japanese Equity Returns

In order to assess the performance of foreign predictors for the Japanese market returns within our context, we report results from simple univariate predictive regressions of dollar- and yen-denominated Nikkei 225 excess returns based on the LJV-US in Panels A and B of Table 6.[15] Moreover, we plot corresponding t(NW) and adjusted R^2 statistics in Figure 7, along with those for the subsample January 2006 to June 2017. For completeness, Panel C provides benchmark results for the dollar-denominated Nikkei returns using the Japanese tail measure LJV-JPN, confirming that this yen-denominated risk measure does not have forecast power for the Nikkei returns, irrespective of the currency denomination. Our first observation is that, unlike the insignificant findings based on LJV-JPN in the previous section, LJV-US does appear to possess moderate forecast power for the Nikkei 225 excess returns measured in yen, even if the evidence is less than compelling. The LJV-US in Panel B yields larger t-values than the corresponding benchmark regressions using the Japanese jump risk component reported in Panel B of Table 4. However, the LJV-US is significantly positive at the 5% level only for forecast horizons of 5-8 months and at the 10% level over longer horizons. Furthermore, the associated R^2 statistics do not surpass 3.75% at any horizon. The results corroborate the hypothesis that the U.S. jump risk component possesses superior predictive ability for the yen-denominated returns relative to the Japanese measure.

[15] The Japanese stock market closes at 3:00 pm Japanese Standard Time (JST), or 1:00 am Eastern Standard Time (EST), before the U.S. markets open. Thus, information released at the end of the month in U.S. cannot be incorporated in Japanese equity prices until the first trading day of the following month. To avoid potentially spurious predictive evidence stemming from this timing issue, we exclude the last day of the month in the U.S., when constructing the U.S. VRP and LJV predictors for the Japanese excess returns.

Nonetheless, the degree of forecast power for the risk premium dynamics of the Japanese equity index seems small compared to the findings for other international equity markets.

In contrast, Panel A of Table 6 and Figure 7 document that the slope coefficients for LJV-US are highly significant at the 5% level for the 2-4 month horizon and the 1% level for the longer horizons in predicting the dollar-denominated Nikkei 225 excess returns. Not only are the t-statistics generally substantially higher than those for predicting the yen-denominated excess returns, but the adjusted R^2's now reach beyond 8% for the full sample and 14% for the subsample period. Thus, contrary to prior findings, this suggest that the Japanese financial markets share important features of predictability with other international indices, especially when expressed in U.S. dollar units. We reiterate that, from Panel C of Table 6, we find that LJV-JPN has no significant predictive power over any horizon for the dollar-denominated Nikkei 225 excess returns.

5.2 U.S. Variance Risk Components and Japanese Equity Returns

Bollerslev et al. (2014) and Londono (2011) focus on the predictive power of the U.S. VRP. Figure 8 reports the predictability patterns from simple regressions of the dollar-denominated Japanese excess returns on VRP-US over the sample from January 2000 to June 2017 and the subsample covering January 2006 – June 2017. We find that the VRP-US has no positive association with the Japanese excess returns whatsoever. Of course, the significantly negative coefficients for the one- and two-month horizons in the longer sample period do yield moderately sized adjusted R^2's, but the negative signs are inconsistent with the implications obtained from basic asset pricing model incorporating the VRP (Bollerslev et al. 2009), and any hint of forecast power for horizons beyond two months is entirely absent. The results in Figures 7 and 8 confirm once more that the U.S. jump tail risk component of the VRP is the relevant quantity for pricing of equity risk compared to the overall VRP. In fact, our findings are consistent with the U.S. jump risk component of VRP constituting an indicator reflecting the global economic environment for downside jump risk compensation.[16]

[16] In empirical results for the U.K. equity market, omitted to conserve space, we also find that the LJV-US helps forecast the FTSE 100 excess returns, expressed in either dollars or pounds.

5.3 Assessing the Impact of Abenomics

For the U.S. and Europe, the evidence supports the predictability of equity-index returns via left tail variation measures, even as the economies have undergone strong business cycle variation and have seen dramatic shifts in the policy regimes, including the onset of highly unconventional monetary policies. Nonetheless, no country has arguably seen as drastic of a change in the conduct of economic policy as Japan through the collection of actions labelled "Abenomics." Specifically, beyond implementing an expansionary monetary policy implying massive quantitative easing and negative interest rates, there have also been policy initiatives that, directly or indirectly, were intended to support the Japanese equity markets. For example, the Bank of Japan (BoJ) decided to purchase a stock market exchange-traded fund (ETF) in 2010, and these purchases escalated from 2013 onwards, leading the BoJ to become a major shareholder in a number of the Nikkei 225 index constituents.[17] In addition, following a reform in 2014, the Japanese Government Pension Investment Fund (GPIF) has increased its holdings of domestic stocks–at the expense of bond holdings–from 12% to 25%.[18] Of course, to the extent these purchases represent buy-and-hold strategies, they will have less of an impact on the overall trading volume. Nonetheless, the question of whether Abenomics has an impact on our predictability results warrants serious consideration.

Direct analysis of the return predictability during the Abenomics period, starting in December 2012, is difficult due to the limited sample period. Instead, we explore whether the inclusion of the Abenomics period in our sample has a material impact on our conclusions. For this purpose, we estimate a univariate version of the predictive regression (14) sequentially, using LJV-US as the sole regressor. We start the sample in January 1996 and initially stop by December 2012, corresponding to the beginning of the Abenomics program. Next, we expand the sample period by one month, adding January 2013, and reestimate the predictive relationship. We continue this procedure all through the end of our sample in 2018.

Figure 9 displays the point estimate for the coefficient of the LJV-US regressor along with its associated Newey-West t- and adjusted R^2-statistic in the 6-month ahead return regressions. The left column refers to the dollar-denominated and the right column to the yen-denominated Nikkei

[17]This policy and some of its consequences are discussed in the Nikkei Asian Review article "BOJ is top-10 shareholder in 40% of Japan's listed companies," June 27, 2018.

[18]See, for example, the account in "World's Biggest Pension Fund Adds $23 Billion as Stocks Rebound," Bloomberg, August 3, 2018.

225 excess returns.[19] We note that the results presented in Section 5.1 refer to the end point of the plot for these series. An interesting conclusion emerges. The inclusion of the Abenomics period has a negative impact on the predictability of the yen-denominated returns, as may be seen in the panels of the right column. In contrast, the significance of the dollar-denominated excess returns is essentially unaltered. In particular, comparing the two columns at the inception point in December 2012, there is only a minor difference between the explanatory power of the LJV-US for the yen- versus dollar-denominated excess returns. This finding confirms the importance of bringing a global perspective to the pricing of Japanese equities.[20]

5.4 Summary

To summarize, this section corroborates the hypothesis that a global left jump risk factor, as captured through the U.S. left jump variation, has significant predictive power for the Japanese market excess returns, especially when expressed in dollar terms. This novel finding brings a global perspective to bear on the issue and seems helpful in terms of shedding light on the risk premium dynamics of the Japanese financial markets. At the same time, our results mirror prior findings in that the local jump tail risk component, presumably reflecting more idiosyncratic Japanese features, as well as the international and local VRPs have no forecast power for the Japanese market excess returns regardless of currency units. Since the critical role of the left tail factor has been established in recent work for other markets, our evidence overcomes the long-standing conundrum that the Japanese markets seem to evade our efforts to confirm return predictability through well-established channels. We document that the dollar-denominated Japanese returns, in fact, are predictable through the identical mechanism as for many foreign equity indices. This suggests that the Japanese financial market is well integrated with the global markets, and is being priced accordingly. On the basis of our findings in Sections 4 and 5, we conjecture that the combination of low correlation between the Japanese and global economic fundamentals and the high degree of integration of the Japanese market are responsible for the apparent stark differences in equity

[19] The results for the corresponding 12-month predictive return regressions are qualitatively identical. The plot for the 12-month excess return horizon is provided in Figure A.5 of the Supplementary Appendix.

[20] Figures A.6 and A.7 of the Supplementary Appendix confirm that predictability does not run in the opposite direction; i.e., the Japanese return and tail variation measures have no significant forecast power for the U.S. equity index returns.

pricing in Japan relative to all other developed international markets. This can also explain the inability of the Japanese option-implied tail measure to predict future US equity returns.

6 Return Predictability for Exchange Rates

In Section 5, we found the LJV-US to be a better predictor for the dollar- than the yen-denominated Nikkei 225 excess returns. Since the former is defined as the sum of the log-return on the dollar-yen exchange rate and the (yen-denominated) Japanese market less the U.S. risk-free rate, this strongly suggests that LJV-US also possesses forecast power for the dollar-yen exchange rate over our sample. Because it is generally very difficult to forecast short- to medium-term currency appreciations, we now directly examine whether the pricing of the jump tail risk component of the VRP may serve as a signal concerning the future evolution in exchange rates.

The literature on predictability of the dollar-yen exchange rate includes numerous studies examining the discrepancy between U.S. and Japanese macroeconomic variables, such as the monetary fundamentals (Mark 1995, Berkowitz and Giorgianni 2001), interest rate (Chen and Tsang 2013), price and inflation, trade balance and output gap (Rossi 2013), among others. Additional predictors explored include net foreign assets (Alquist and Chinn 2008, Della Corte et al. 2012) and commercial paper (Adrian et al. 2015).[21] On the other hand, Londono and Zhou (2017) examine the predictive power of world currency and stock variance risk premiums for 22 foreign exchange rates versus the U.S. dollar from 2000 to 2011. The results for the individual-currency regressions show that these predictors have weak or non-existent forecast power for the dollar-yen exchange rate as, again, Japan is one of only a few outliers. This is consistent with our prior findings that the VRP has only weak explanatory power for the Nikkei 225, whereas the left tail measure has superior predictive ability. Hence, we test the hypothesis that the U.S. left jump variation or the gap between the U.S. and Japanese left jump variation have forecast power for the dollar-yen exchange returns. Towards that end, we explore the following predictive regressions for exchange rate returns,

$$\frac{1}{h} R_{t,t+h} \; = \; \beta_0(h) \, + \, \beta_1(h) \, V_t \, + \, u_{t,t+h}, \quad t = 1, \ldots, T, \tag{16}$$

where $R_{t,t+h}$ denotes $h = 1$ (one month) to $h = 12$ (one year) returns for the dollar-yen exchange

[21] Table A.3 of the Supplementary Appendix summarizes the findings from a number of these studies.

rate and the error term satisfies the martingale difference condition in (15). V_t refers to one or more explanatory variables, including predictors such as LJV-US and the LJV differential, LJV-US − LJV-JPN.

We report the results from univariate regressions of the dollar-yen exchange rate returns on LJV-US in Figure 10. The solid line in the left figure indicates that LJV-US is significant at the 10% level for the eight-month horizon over the full sample, January 1996 to June 2017. The positive coefficient estimates imply that an increase in the U.S. risk-neutral left jump tail variation is correlated with a future depreciation of the U.S. dollars versus the yen. The solid line in the right panel shows that the corresponding adjusted R^2's surpass 5% at the eleven-month horizon. For the corresponding winsorized regressions, the dashed line indicates that LJV-US is significant at the 5% level after eight months, and the adjusted R^2 exceeds 6.6% at the eleven-month horizon. These findings suggest that the jump risk component of the U.S VRP, indeed, might have a moderate degree of predictive power for the future dollar-yen exchange rate. This is an interesting hypothesis to explore more widely, but we do not pursue it further here.

Figure 11 plots the Newey–West t-statistics from multiple regressions based on both the diffusive (dashed line) and jump risk component (solid line) of the VRP along with the corresponding adjusted R^2 over the sample period January 2000 – June 2017. The VRP-US appears to provide incremental predictive power over horizons from eight to twelve months. The positive coefficients imply that an increase in VRP-US tends to be followed by a depreciation of the dollar, consistent with the impact of the jump risk component. We also note that LJV-US remains significant at the nine-month horizon and the corresponding adjusted R^2's exceed those from the univariate LJV-US regressions. It suggests that the diffusive and jump risk components each contain independent information regarding the future relative valuation of the U.S. dollar and Japanese yen.[22]

7 Conclusion

In this paper we study the return predictability for the Japanese stock market using risk measures constructed from U.S. and Japanese equity index option data. We find that risk measures

[22]One common predictor for exchange returns is the relative interest rates. Figure A.4 of the Supplementary Appendix shows that our findings are robust to the inclusion of the dollar-yen interest rate differential in the predictive exchange rate regressions.

constructed from Japanese options show very weak predictive ability for the future excess returns on the Nikkei 225 index. On the other hand, a negative tail risk measure constructed from U.S. equity index options has some predictive ability for future Japanese stock market returns. The predictive ability of this U.S. left tail measure strengthens significantly, and is comparable to that for the U.S. stock market, when denominating the Japanese stock market returns in dollars, i.e., when considering the investment in the Japanese stock market from the point of view of a foreign investor. Consistent with evidence for the U.S., we find that variance risk premium measures have no extra predictive ability for stock market returns beyond the one contained in their negative tail component. Finally, we find evidence of limited predictability for the dollar-yen exchange rate. The marginal-to-moderate degree of significance for the yen-denominated Nikkei excess returns and the exchange rate, but substantially stronger evidence for the dollar-denominated Nikkei returns, points to an important role for the interaction between the currency and Japanese equity markets in rationalizing our results.

There are a few potential caveats associated with our evidence. From a theoretical perspective, we manage to avoid strong distributional assumptions by relying on largely nonparametric measures for the risk-neutral return and tail variation. Nonetheless, we do rely on the imposition of a power law distribution for the risk-neutral tail observations. We do not find this feature troublesome, as the assumption of a log-linear tail lines up very well with the observed OTM option prices.

Another issue for predictive regressions is the ever-present concern regarding data snooping. In this context, we have a number of alleviating factors. First, the predictive ability of option-implied tail measures is implied by number of existing equilibrium asset pricing models. Second, the Japanese market is less correlated with other national markets than is typical for well-developed market throughout the world, so the Japanese experience provides useful incremental evidence. Third, findings from other countries already indicate that the left-tail variation measure should possess forecast power for the equity-index returns; yet prior studies have failed to document any such predictive relation in Japan based on the variance risk premium, which embeds our tail variation measure. Hence, arguably, one would not expect, a priori, that a non-trivial amount of predictability could be detected.

Finally, from a purely empirical perspective, we have only a short sample period available for the Japanese equity-index options. Moreover, there is a possible structural break in the series, given the dramatic shift in economic policy associated with the adoption of "Abenomics." Nonetheless, we are able to establish statistically significant return predictability. At some level, this may not be too surprising as unconventional economic policies also were adopted across many other countries, and the return predictability patterns were documented both before and after the implementation of such shifts in most cases. In fact, for the Japanese case, we find that the yen-denominated excess returns become hard to predict after the adoption of Abenomics, yet the dollar-denominated returns continue to display a similar degree of correlation with our U.S. tail variation measure. Even so, the small sample issue is not innocuous. Ultimately, only time will tell whether our findings are fully robust, especially during periods of highly unconventional economic policies such as Abenomics.

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Table 1: Summary Statistics for Monthly Market Excess and Exchange Rate Returns

Panel A: Univariate Return Statistics

	S&P 500	DDNikkei 225	Nikkei 225	Dollar/Yen
Sample size	258	258	258	258
Mean	0.50	−0.10	0.08	−0.01
Std. Dev.	4.35	5.54	5.69	3.03
Skewness	−0.82	−0.35	−0.69	0.48
Kurtosis	4.61	3.28	4.26	5.52
Minimum	−18.42	−19.57	−27.25	−8.93
Maximum	10.37	16.45	12.19	15.62
ACF(1)	0.08	0.12	0.11	0.01

Panel B: Contemporaneous Correlations

	S&P 500	DDNikkei 225	Nikkei 225	Dollar/Yen
S&P 500	1			
DDNikkei 225	0.58	1		
Nikkei 225	0.60	0.85	1	
Dollar/Yen	−0.06	0.22	−0.32	1

Note: The statistics are generated from sample data covering February 1996 to July 2017. DDNikkei is the Nikkei 225 excess return in U.S. dollars. The market excess returns are reported in monthly percentage form. The ACF(1) is the first-order sample autocorrelation coefficient of the monthly returns. The contemporaneous correlations of the monthly return series are obtained for the corresponding sample period.

Table 2: Nikkei 225 Out-of-the-Money Index Option Data

Panel A: Sorted by						
Time-to-maturity τ	$[8, 30)$	$[30, 45)$	$[45, 60)$	$[60, 75)$	$[75, 90)$	All
Call option						
Average number per trading day	10.60	14.22	15.75	15.78	14.73	36.42
Average percentage bid-ask spread	17.43	15.64	15.06	18.82	18.40	17.00
Average implied volatility	24.85	23.02	22.62	21.83	21.41	22.82
Put option						
Average number per trading day	16.87	20.21	21.27	20.36	18.54	50.57
Average percentage bid-ask spread	17.23	13.86	12.95	15.46	15.26	15.00
Average implied volatility	36.75	34.56	33.65	33.32	32.47	34.36

Panel B: Sorted by	OTM Put			OTM Call		
Moneyness K/F	< 0.9	$[0.9, 0.97)$	$[0.97, 1.03)$	$[1.03, 1.1)$	$>= 1.1$	All
Near-term option						
Average number per trading day	10.51	4.96	4.26	4.83	4.50	29.06
Average percentage bid-ask spread	23.17	7.11	4.00	11.60	28.53	16.53
Average implied volatility	42.99	27.16	22.28	21.24	28.76	31.43
Next-term option						
Average number per trading day	14.02	4.91	4.19	4.93	8.57	36.62
Average percentage bid-ask spread	18.22	4.98	3.56	6.09	24.67	14.64
Average implied volatility	38.58	24.98	22.03	20.52	23.95	29.01

Panel C: Sorted by	OTM Put, $\tau \in [8, 44]$				OTM Call, $\tau \in [8, 44]$	
$log(K/F)/(\sqrt{\tau}\sigma_t^{ATM})$	< -2.5	$[-2.5, -2.0)$	$[-2.0, -1.5)$		$[1.0, 1.5)$	$>= 1.5$
[Jan. 2006, Nov. 2008]						
Average number per week	14.19	4.88	4.88		6.86	12.81
[Dec. 2008, Jun. 2017]						
Average number per week	45.05	9.98	10.70		13.19	29.36

Note: The table summarizes the Nikkei out-of-the-money index option data sorted by maturity and moneyness from January 2006 to June 2017. Panel A reports the average number of OTM options with non-zero bid and ask quotes available per trading day, whenever options of the given tenor category are traded. The average percentage bid-ask spread is a simple average of 100 $\times$(ask $-$ bid)/ask. The average implied volatility is the average of the annual percentage Black-Scholes implied volatility for each moneyness level (the ratio of the strike price, K, to forward price, F). Panel B reports the same three measures for the near- and next-term options sorted by moneyness. Panel C provides the average number of shorter-dated options available per week as a function of moneyness, where σ_t^{ATM} refers to the end-of-day t at-the-money Black Scholes implied volatility.

Table 3: Descriptive Statistics for the Variance Risk Premium and its Jump Tail Component

Panel A: Univariate statistics

	VRP-US	VRP-JPN	LJV-US	LJV-JPN
Sample size	210	138	258	138
Mean	0.14	0.39	0.05	0.05
Std. Dev.	0.16	0.55	0.05	0.06
Skewness	0.52	6.62	3.42	3.17
Kurtosis	12.27	57.76	17.71	15.70
Minimum	−0.71	0.05	0.01	0.00
Maximum	0.99	5.50	0.37	0.43
ACF(1)	0.34	0.58	0.68	0.60

Panel B: Contemporaneous correlations

	VRP-US	VRP-JPN	LJV-US	LJV-JPN
VRP-US	1			
VRP-JPN	−0.17	1		
LJV-US	0.03	0.76	1	
LJV-JPN	0.17	0.22	0.49	1

Note: The monthly samples cover January 1996 to June 2017 for LJV-US, January 2000 to June 2017 for VRP-US and January 2006 to June 2017 for the two Japanese series. They are reported in monthly percentage form. The ACF(1) is the first-order sample autocorrelation. The contemporaneous correlations are obtained for the period January 2006 to June 2017.

Table 4: Country-Specific Simple Return Predictability Regressions

Panel A: Predicted variable: S&P 500 excess returns												
h	1	2	3	4	5	6	7	8	9	10	11	12
Const	0.42	0.23	0.26	0.22	0.12	0.11	0.11	0.12	0.16	0.14	0.15	0.16
t(NW)	(0.92)	(0.53)	(0.67)	(0.61)	(0.32)	(0.28)	(0.27)	(0.30)	(0.37)	(0.33)	(0.36)	(0.38)
LJV-US	1.71	5.57	4.98	5.91	8.09	8.27	8.48	8.16	7.39	7.77	7.48	7.33
t(NW)	(0.18)	(0.61)	(0.63)	(0.94)	(1.93^c)	(2.56^b)	(2.72^a)	(2.58^b)	(2.08^b)	(2.34^b)	(2.32^b)	(2.44^b)
b(LLSW)	(0.22)	(0.84)	(0.84)	(1.19)	(2.34^b)	(2.68^b)	(2.69^b)	(2.53^b)	(2.03^c)	(2.32^b)	(2.33^b)	(2.47^b)
t(LLSW)	(0.22)	(0.85)	(0.87)	(1.27)	(2.60^b)	(3.03^a)	(3.00^a)	(2.82^b)	(2.21^b)	(2.51^b)	(2.51^b)	(2.63^b)
Adj. R^2	−0.36	0.26	0.40	1.03	2.80	3.44	4.24	4.45	3.97	4.90	4.97	5.17
Panel B: Predicted variable: Nikkei 225 excess returns												
Const	0.17	0.15	0.14	0.09	0.09	0.05	0.07	0.13	0.16	0.12	0.12	0.10
t(NW)	(0.23)	(0.21)	(0.19)	(0.12)	(0.12)	(0.07)	(0.09)	(0.17)	(0.21)	(0.17)	(0.16)	(0.14)
LJV-JPN	1.80	2.16	2.39	3.67	4.15	5.21	5.12	4.05	3.51	4.18	4.33	4.58
t(NW)	(0.28)	(0.35)	(0.35)	(0.53)	(0.57)	(0.77)	(0.83)	(0.68)	(0.62)	(0.77)	(0.83)	(0.90)
b(LLSW)	(0.23)	(0.26)	(0.29)	(0.46)	(0.53)	(0.73)	(0.81)	(0.68)	(0.64)	(0.81)	(0.89)	(0.98)
t(LLSW)	(0.24)	(0.28)	(0.30)	(0.47)	(0.54)	(0.75)	(0.83)	(0.70)	(0.65)	(0.82)	(0.89)	(0.97)
Adj. R^2	−0.70	−0.64	−0.56	−0.21	0.07	0.74	0.94	0.48	0.29	0.88	1.16	1.56

Note: The table reports on univariate predictability regressions for aggregate stock excess returns based on our local jump tail risk component of the VRP measure in equation (13). The predictors cover January 1996 to June 2017 for U.S. and January 2006 to June 2017 for Japan. In parentheses, we present t(NW), the NW t-statistics with a lag length of $2h$, while b(LLSW) and t(LLSW) are the NW and EWC based-statistics proposed by Lazarus et al. (2018). The superscripts a, b and c indicate the significance levels [$p < 0.01$], [$p < 0.05$] and [$p < 0.1$], respectively. The adjusted R^2's are reported in percentage form.

Table 5: Ratio of Foreign Investors on Trading Values

Year	TSE 1st Section stocks	ETFs	Nikkei 225 futures	Nikkei 225 put options	Nikkei 225 call options
2007	63.3	47.4	72.5	86.3	83.1
2008	64.8	47.8	78.7	86.1	85.6
2009	53.9	43.8	77.5	91.6	90.3
2010	63.6	54.5	76.7	89.7	88.9
2011	67.8	49.0	79.0	90.8	92.5
2012	67.7	51.4	77.4	93.7	92.9
2013	62.3	54.9	80.8	93.9	94.6
2014	69.1	53.9	81.0	92.9	94.3
2015	71.2	54.6	78.3	90.4	91.9
2016	73.8	62.9	79.5	92.5	93.9
2017	72.5	61.5	81.7	93.9	92.9

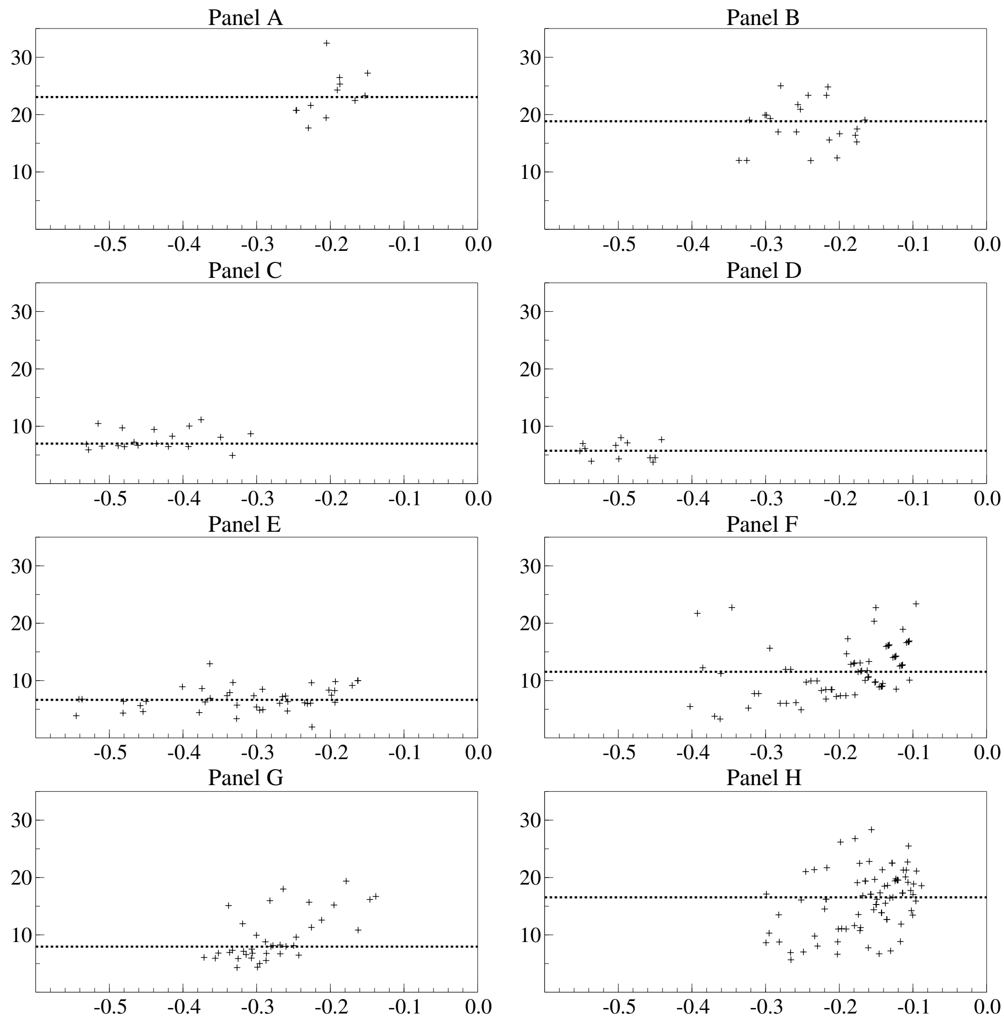
Note: This table reports the percentage of foreign investors in the total brokerage trading value (breakdown of brokerage). Survey by the Japan Exchange Group results from trading participants with capital of at least 3 billion yen, see https://www.jpx.co.jp/english/markets/statistics-equities/investor-type/00-02.html and https://www.jpx.co.jp/english/markets/statistics-derivatives/sector/02.html for details.

Table 6: The Dollar Denominated and Local Nikkei 225 Return Predictability Regressions

Panel A: Predicted variable: Dollar denominated Nikkei 225 excess returns, Predictor: LJV-US												
h	1	2	3	4	5	6	7	8	9	10	11	12
Const	−0.46	−0.73	−0.59	−0.63	−0.74	−0.79	−0.82	−0.75	−0.69	−0.67	−0.65	−0.63
t(NW)	(−0.81)	(−1.34)	(−1.17)	(−1.27)	(−1.48)	(−1.53)	(−1.54)	(−1.39)	(−1.26)	(−1.23)	(−1.20)	(−1.15)
LJV-US	7.35	12.92	10.08	10.94	13.34	14.47	15.23	14.00	12.72	12.49	12.28	11.87
t(NW)	(0.80)	(1.65^c)	(1.49)	(1.85^c)	(3.00^a)	(3.70^a)	(3.94^a)	(3.70^a)	(3.28^a)	(3.27^a)	(3.15^a)	(2.98^a)
b(LLSW)	(1.17)	(2.11^c)	(1.80^c)	(2.12^c)	(3.11^a)	(3.56^a)	(3.72^a)	(3.53^a)	(3.19^a)	(3.23^a)	(3.19^a)	(3.09^a)
t(LLSW)	(1.28)	(2.50^b)	(2.14^b)	(2.47^b)	(3.60^a)	(3.91^a)	(3.97^a)	(3.75^a)	(3.37^a)	(3.42^a)	(3.41^a)	(3.29^a)
Adj. R^2	−0.01	1.70	1.50	2.36	4.57	6.34	8.08	7.67	6.90	7.18	7.52	7.63
Panel B: Predicted variable: Yen denominated Nikkei 225 excess returns, Predictor: LJV-US												
Const	0.02	−0.23	−0.18	−0.30	−0.39	−0.43	−0.43	−0.35	−0.28	−0.25	−0.22	−0.22
t(NW)	(0.03)	(−0.44)	(−0.35)	(−0.59)	(−0.71)	(−0.75)	(−0.75)	(−0.60)	(−0.48)	(−0.42)	(−0.38)	(−0.38)
LJV-US	1.29	6.47	5.29	7.92	9.76	10.62	10.87	9.38	7.92	7.33	6.80	6.82
t(NW)	(0.17)	(1.03)	(0.98)	(1.74^c)	(2.40^b)	(2.63^a)	(2.67^a)	(2.21^b)	(1.77^c)	(1.70^c)	(1.67^c)	(1.74^c)
b(LLSW)	(0.21)	(1.36)	(1.17)	(1.87^c)	(2.28^b)	(2.38^b)	(2.44^b)	(2.07^c)	(1.71)	(1.68)	(1.68)	(1.79^c)
t(LLSW)	(0.23)	(1.63)	(1.42)	(2.23^b)	(2.47^b)	(2.53^b)	(2.58^b)	(2.17^b)	(1.79^c)	(1.76^c)	(1.76^c)	(1.87^c)
Adj. R^2	−0.38	0.11	0.08	0.95	2.06	3.00	3.73	3.13	2.41	2.24	2.07	2.28
Panel C: Predicted variable: Dollar denominated Nikkei 225 excess returns, Predictor: LJV-JPN												
Const	0.06	0.08	0.03	−0.05	−0.04	−0.05	−0.01	0.06	0.11	0.10	0.12	0.12
t(NW)	(0.11)	(0.16)	(0.07)	(−0.10)	(−0.08)	(−0.09)	(−0.02)	(0.12)	(0.22)	(0.21)	(0.24)	(0.24)
LJV-JPN	3.41	3.03	3.84	5.62	5.89	6.33	6.02	4.83	4.02	4.29	4.09	4.14
t(NW)	(0.56)	(0.55)	(0.66)	(0.95)	(0.92)	(0.98)	(0.97)	(0.82)	(0.73)	(0.85)	(0.85)	(0.89)
b(LLSW)	(0.58)	(0.48)	(0.59)	(0.85)	(0.85)	(0.93)	(0.95)	(0.82)	(0.75)	(0.89)	(0.91)	(0.97)
t(LLSW)	(0.62)	(0.50)	(0.60)	(0.86)	(0.86)	(0.94)	(0.96)	(0.83)	(0.76)	(0.91)	(0.93)	(0.99)
Adj. R^2	−0.51	−0.42	0.07	1.59	2.38	3.49	3.78	2.64	1.91	2.61	2.66	3.19

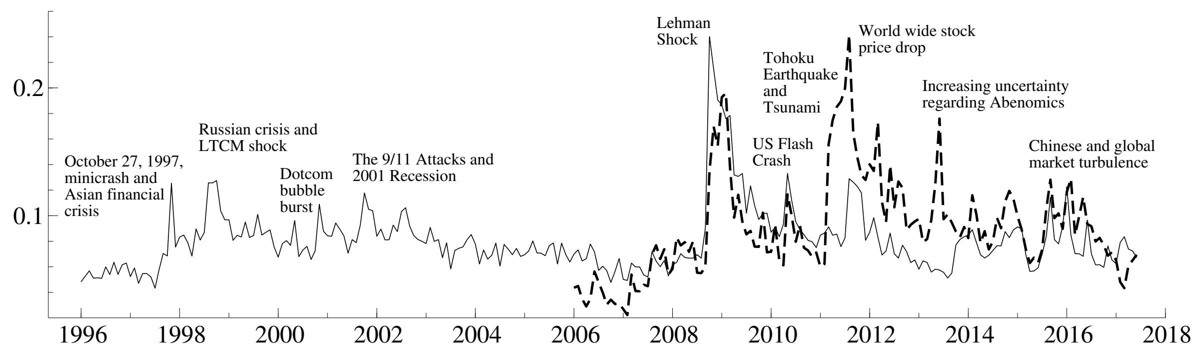
Note: The table reports on univariate predictability regressions for aggregate stock excess returns based on our local jump tail risk component of the VRP measure in equation (13) for the U.S. or Japan. The predictors cover January 1996 to June 2017 for U.S. and January 2006 to June 2017 for Japan. In parentheses, we present t(NW), the NW t-statistics with a lag length of $2h$, while b(LLSW) and t(LLSW) are the NW and EWC based-statistics proposed by Lazarus et al. (2018). The superscripts a, b and c indicate the significance levels [$p < 0.01$], [$p < 0.05$] and [$p < 0.1$], respectively. The adjusted R^2's are reported in percentage form.

Figure 1: Slopes of the OTM Nikkei 225 Index Put Decay



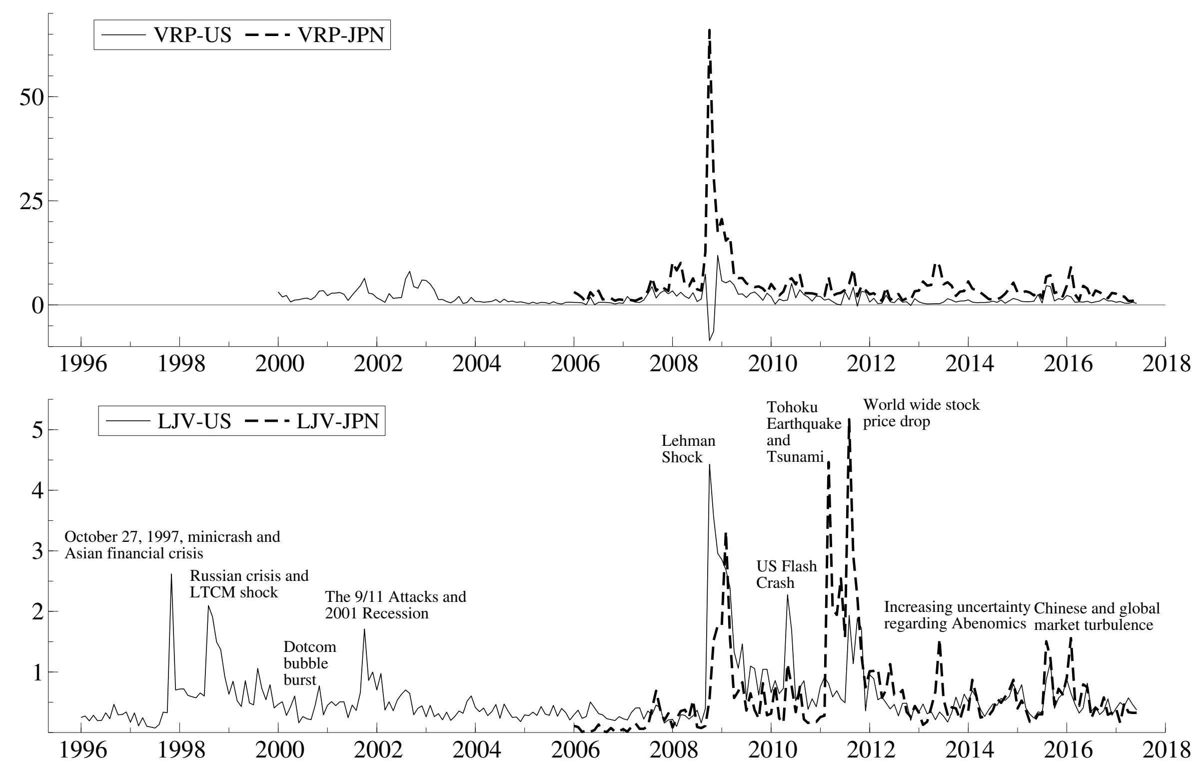
Note: The figure plots estimated weekly slopes of the OTM put decay, obtained as $\log(O_{t,\tau}(k_{t,i})/O_{t,\tau}(k_{t,i-1}))/(k_{t,i} - k_{t,i-1})$ against log-moneyness $k_{t,i}$ under the assumption that the shape of the left jump tails are constant over each individual week. The flat dotted lines represent the estimated values of $1+\alpha^{-}$. The plots are obtained by pooling the selected Nikkei 225 OTM put options over the week from January 18 to 24, 2006 (Panel A), December 8 to 14, 2007 (Panel B), November 22 to 28, 2008 (Panel C), December 10 to 16, 2008 (Panel D), March 25 to 31, 2011 (Panel E), August 16 to 22, 2014 (Panel F), September 3 to 9, 2015 (Panel G), and June 10 to 16, 2017 (Panel H), respectively.

Figure 2: Plots of Left Jump Tail Estimates of $1/\alpha_t^-$



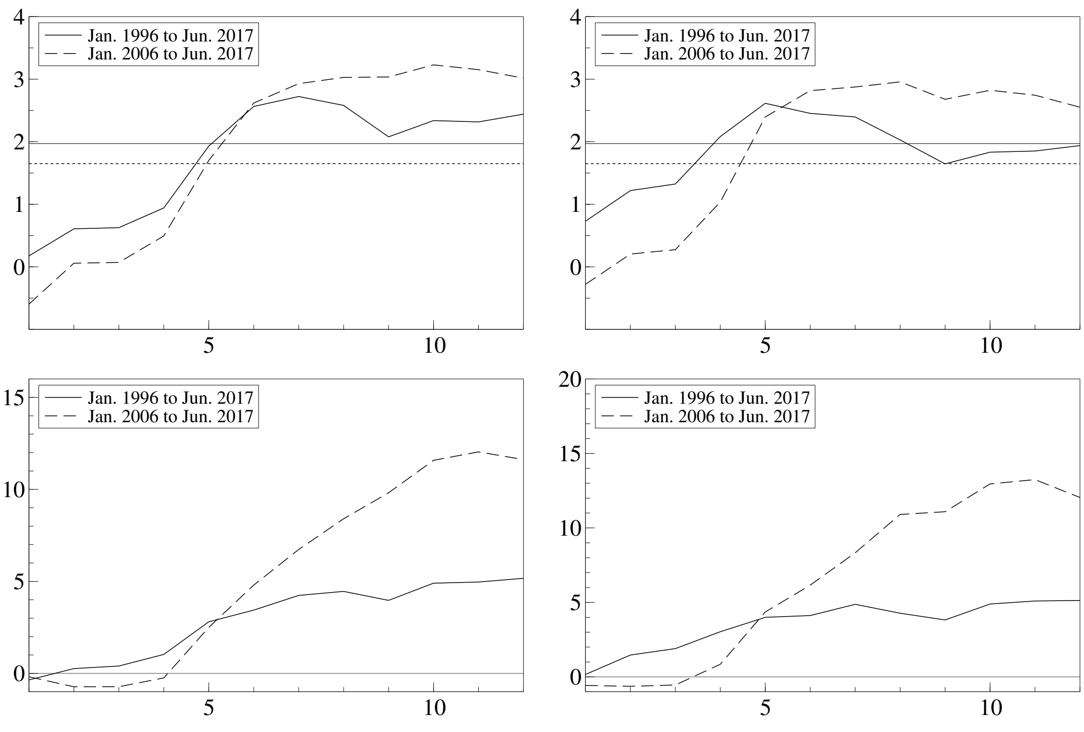
Note: The figure plots the estimates of $1/\alpha_t^-$ at a monthly frequency over the sample from January 1996 to June 2017 for U.S. (solid line) and January 2006 to June 2017 for Japan (dashed line).

Figure 3: Plots of Variance Risk Premium and its Jump Tail Component



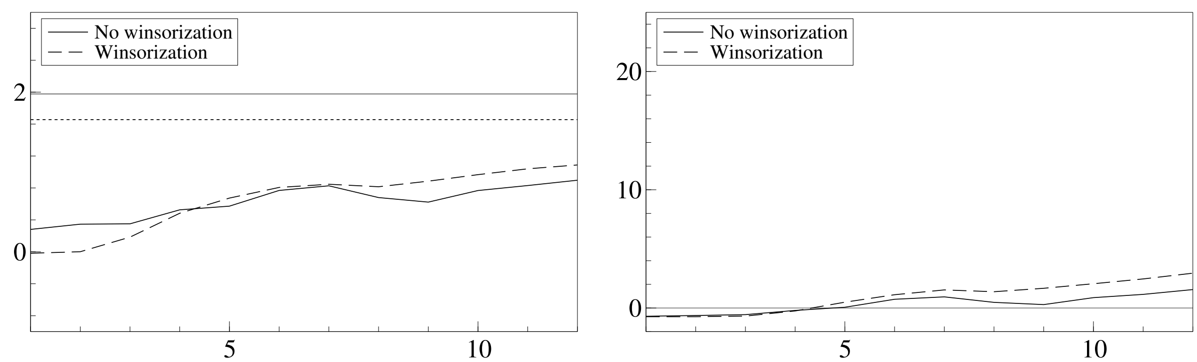
Note: The series are plotted at a monthly frequency. They span January 1996 to June 2017 for LJV-US, January 2000 to June 2017 for VRP-US, and January 2006 to June 2017 for Japan. They are reported in annualized percentage form.

Figure 4: Country-Specific Simple Return Predictability Regressions for U.S.



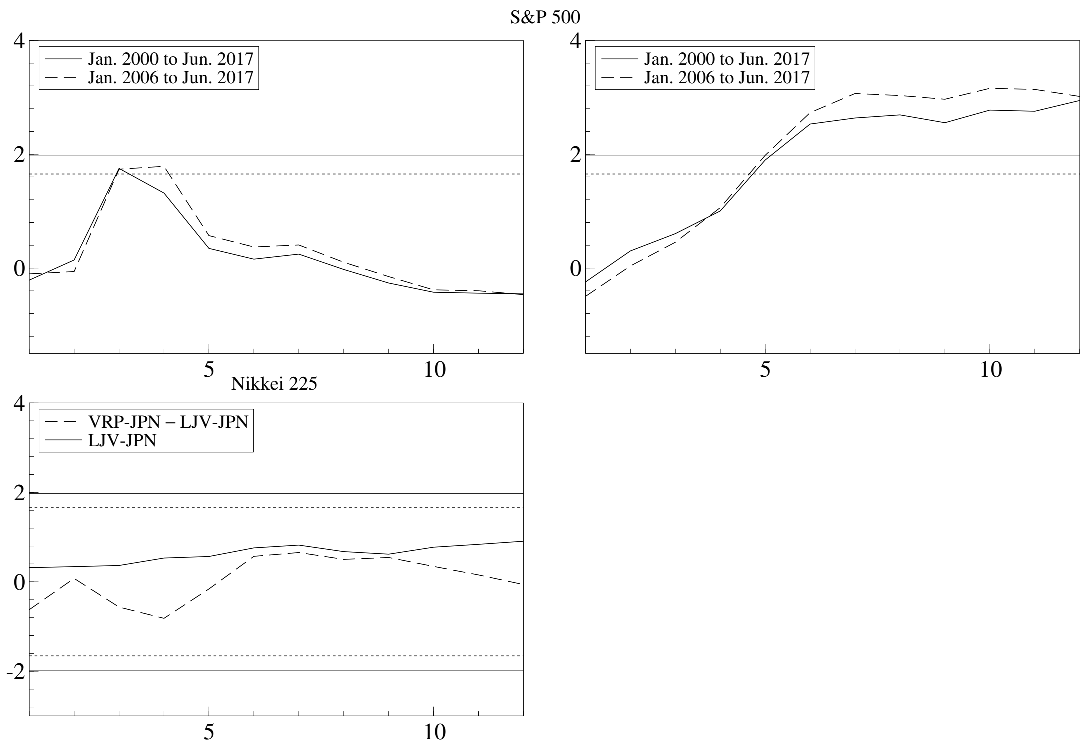
Note: The upper (lower) left panels depict the Newey–West t-statistics, t(NW), (adjusted R^2's) from univariate regressions of the S&P 500 excess returns over a 1-12 month horizon based on LJV-US for the full sample, January 1996 to June 2017, and a subsample from January 2006 to June 2017. The right panels provide results from corresponding robust regressions, where the dependent and independent variables are winsorized at the 2.5% and 97.5% levels.

Figure 5: Country-Specific Simple Return Predictability Regressions for Japan.



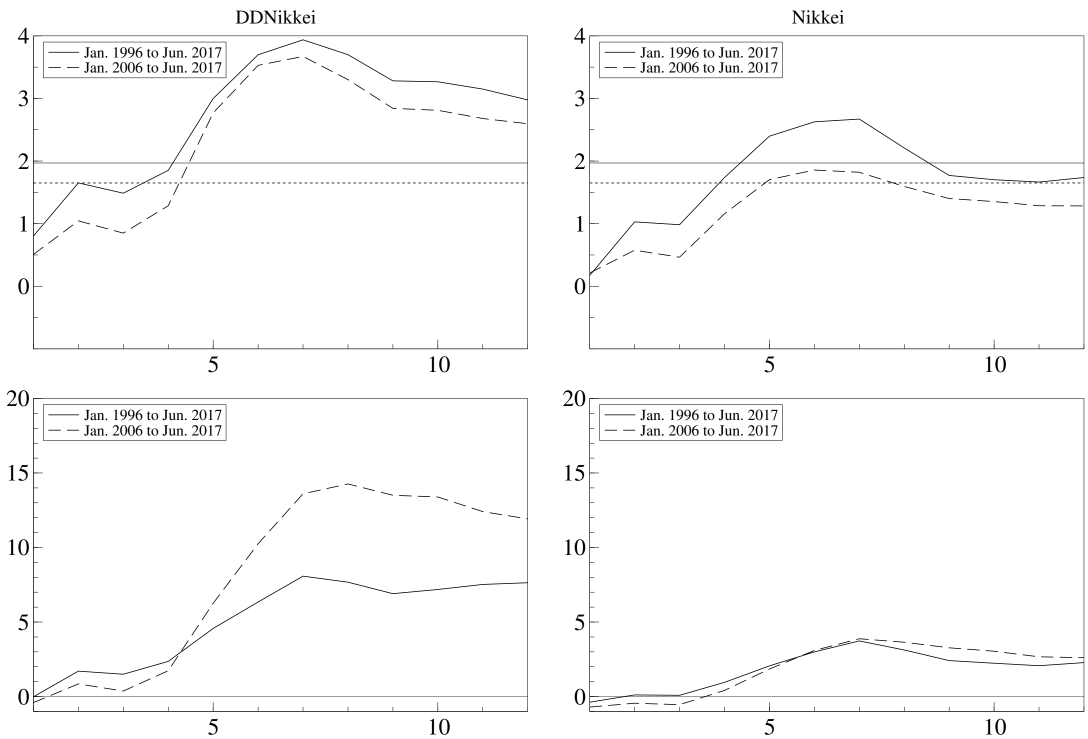
Note: The left and right panels depict the Newey–West t-statistics, t(NW), and adjusted R^2's from univariate regressions of the Nikkei 225 excess returns over a 1-12 month horizon based on LJV-JPN from January 2006 to June 2017. The solid lines are based on the regression results in Panel B of Table 4. The dashed lines represent results from corresponding robust regressions using the dependent and independent variables winsorized at the 2.5% and 97.5% levels.

Figure 6: Country-Specific Multiple Return Predictability Regressions



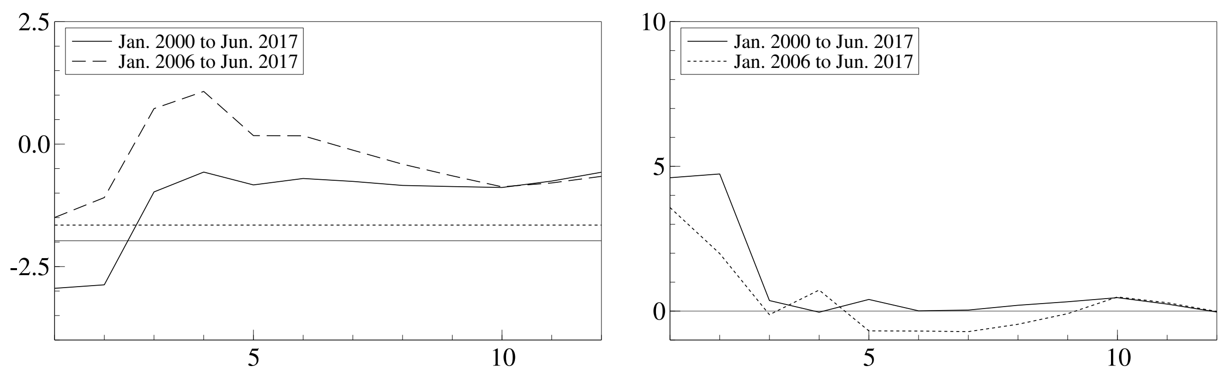
Note: The upper panels plot the Newey–West t-statistics, t(NW), from multiple regressions based on the monthly measures for the U.S. diffusive risk component $VRP - LJV$ (left) and jump risk component LJV (right). The lower panel represents t(NW) from multiple regressions based on the monthly $VRP - LJV$ (dashed lines) and LJV (solid lines) measures for Japan.

Figure 7: Dollar- and Yen-Denominated Nikkei 225 Return Regressions Based on LJV-US



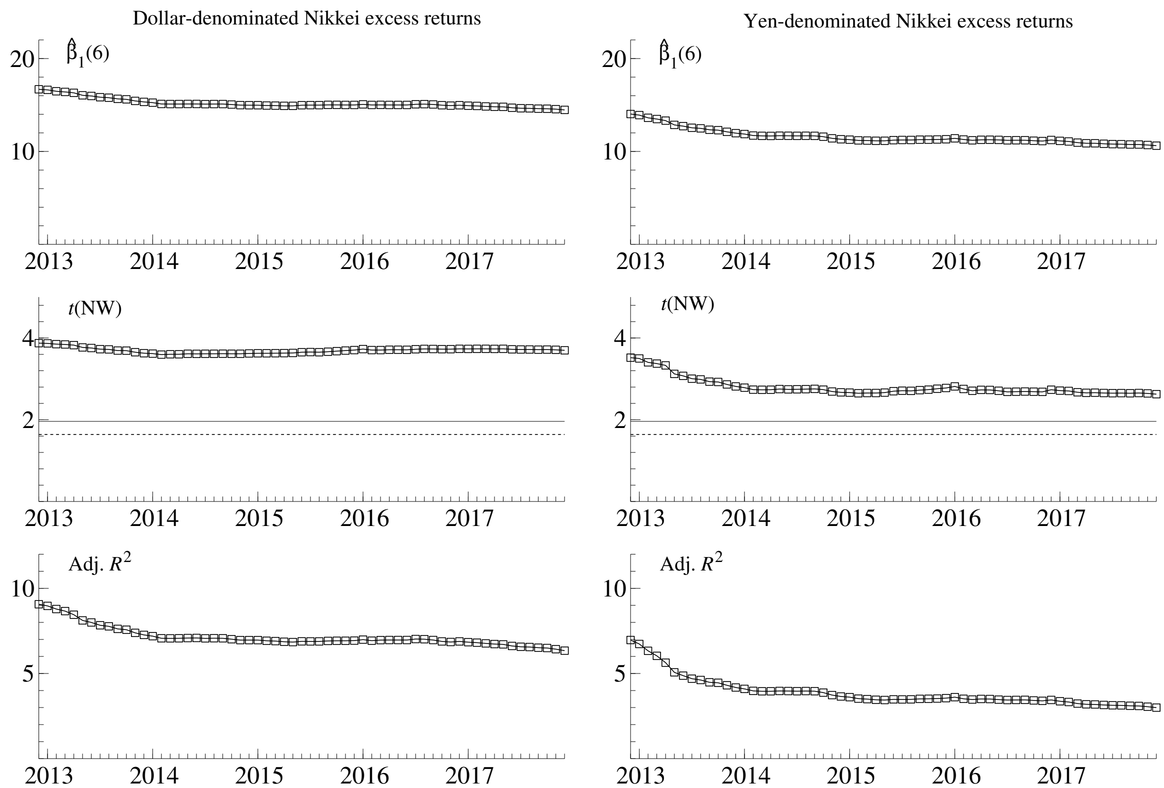
Note: The upper (lower) left and right panels depict the Newey–West t-statistics, t(NW) (adjusted R^2's), from univariate regressions of the dollar-denominated and local (yen-denominated) Nikkei 225 excess returns over a 1-12 month horizon based on LJV-US for the full sample, January 1996 to June 2017, and a subsample, January 2006 to June 2017, respectively.

Figure 8: Dollar-Denominated Nikkei 225 Return Regressions Based on VRP-US



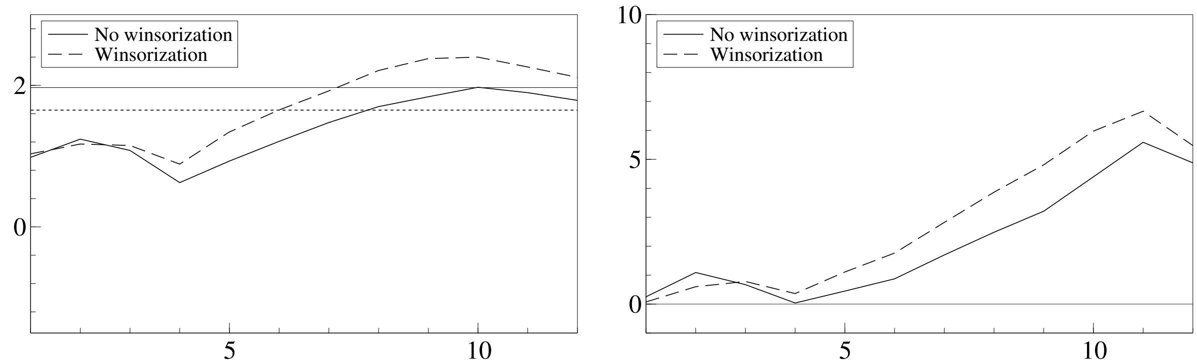
Note: The left and right panels represent the Newey–West t-statistics, t(NW), and adjusted R^2's from univariate regressions of the excess returns for the dollar denominated Nikkei 225 over a 1-12 month horizon based on VRP-US for the sample, January 2000 to June 2017, and a subsample covering January 2006 to June 2017.

Figure 9: Sequential Dollar-Denominated Nikkei 225 Return Regressions Based on LJV-US



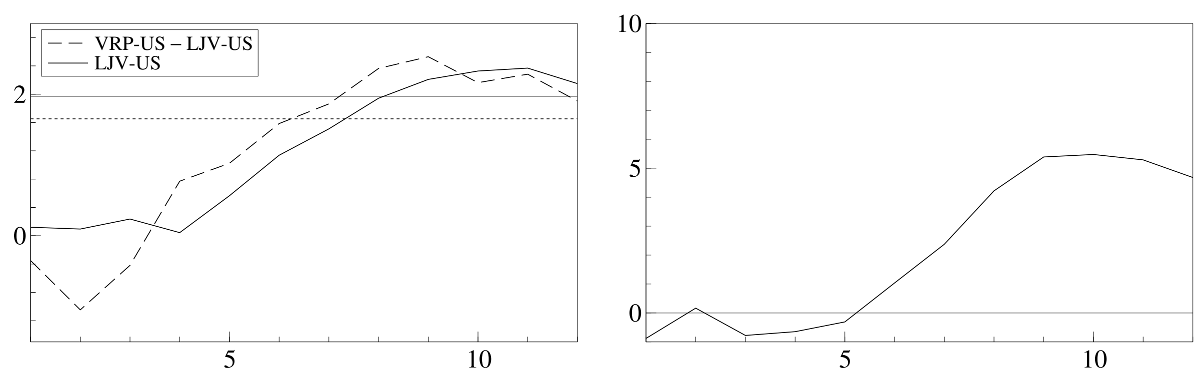
Note: Time series plots of $\hat{\beta}_1(6)$, t(NW) and adjusted R^2 for predictability regressions of dollar- and yen-denominated Nikkei 225 excess returns based on LJV-US over a horizon of 6 months, as the end point of the excess return series moves from December 2012 to December 2017.

Figure 10: Dollar-Yen Exchange Rate Return Predictability Based on LJV-US



Note: The left and right panels plot the Newey–West t-statistics, t(NW), and adjusted R^2's from univariate regressions of the dollar-yen exchange rate returns over a 1-12 month horizon based on LJV-US for the full sample, January 1996 to June 2017 (solid lines). The dashed lines represent results from robust regressions using the dependent and independent variables winsorized at the 2.5% and 97.5% levels.

Figure 11: Dollar-Yen Exchange Rate Return Predictability Based on Diffusive and Jump Risk Components of VRP-US



Note: The left panels represent the Newey–West t-statistics, t(NW), from multiple return predictability regressions of the dollar-yen exchange rates over a 1-12 month horizon based on the diffusive risk component, VRP-US $-$ LJV-US, and jump risk component LJV-US for the sample from January 2000 to June 2017. The right panels plot the corresponding adjusted R^2's.