International stock return predictability: The role of U.S. volatility risk

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ABSTRACT

We study the impact of U.S. equity volatility risk on international equity risk premia. A common factor constructed from the term structure of U.S. option-implied equity forward variances consistently predicts stock returns on the U.S. and 10 non-U.S. industrialized countries both in- and out-of-sample. The predictive power of the U.S. forward variance factor is stronger when the U.S. volatility spillover intensity is higher or when global stock markets are more connected. Empirically, the U.S. volatility risk can predict local economic conditions and economic uncertainty, suggesting that the predictability arises from the link between the U.S. volatility risk and changing gloal investment opportunities. Overall, our evidence is consistent with an intertemporal capital asset pricing model and underscores the role of the U.S. equity volatility in shaping the international risk-return tradeoff.

***JEL classification*: G12; G13; G15; G17**

***Keywords*: International equity markets, Risk-return tradeoff, U.S. volatility risk, Forward variance, Term structure**

1 Introduction

The risk-return relation is a fundamental issue in finance. In his seminar research of asset pricing theory, Merton (1973) develops an intertemporal capital asset pricing model (ICAPM) in which the expected market excess return is determined by its own conditional variance as well as its conditional covariance with state variables that describe changes in investment opportunity set. In particular, the model prescribes a *partial* positive relation between the conditional market risk premium and the conditional market variance, which has triggered a large empirical literature studying this risk-return relation. Whereas earlier studies often reached mixed or even contradictory evidence, recent research tends to agree upon that this relation holds for the U.S. equity market conditionally (Bali, 2008; Bali and Engle, 2010; Bali and Peng, 2006; Ghysels, Santa-Clara, and Valkanov, 2005; Guo and Whitelaw, 2006; Ludvigson and Ng, 2007; Rossi and Timmermann, 2015).[1]

To the best of our knowledge, how the U.S. volatility risk affects international equity risk premia has not been thoroughly studied yet. The past three decades have witnessed an increasing degree of economic integration and financial openness around the world. Given that the United States is the world's largest economy and it maintains tight relations with other countries through bilateral trades and direct foreign investments, a positive shock to U.S. volatility is likely a global shock that can pass through other markets and affect global investment opportunities. Besides, there is a large literature documenting volatility spillover from the U.S. stock market to other markets (Baele, 2005; Hamao, Masulis, and Ng, 1990). In particular, Yang and Zhou (2017) uncover that the U.S. stock market is at the center of the international volatility spillover network and the spillover intensity has been intensified since 2008. From the perspective of cross-country volatility transmissions, the U.S. volatility variation is key to the global volatility risk dynamics (Buncic and Gisler, 2016). According to an international version of ICAPM, the U.S. equity volatility risk should be priced in the global equity market.

In this paper, we study the intertemporal relation between the U.S. volatility risk and the international market excess returns. To this end, we build a U.S. volatility risk factor from the model-free forward variances implied from the S&P 500 option prices. As shown

[1]This literature is too large to be summarized but see the review of Lettau and Ludvigson (2010).

by Busch, Christensen, and Nielsen (2011) and Jiang and Tian (2005), among others, the option-implied variance is forward-looking and exhibits superior predictive power for realized variance relative to the variance based on historical return data.[2] In addition, the option-implied (forward) variance has a term structure feature that contains rich predictive information about the equity premium (Andreou, Kagkadis, Philip, and Taamouti, 2019; Bakshi, Panayotov, and Skoulakis, 2011; Feunou, Fontaine, Taamouti, and Tédongap, 2014; Luo and Zhang, 2017). We construct the model-free U.S. forward variances covering the S&P 500 return variation over three to six, six to nine, nine to 12, and 12 to 18 months ahead, and we apply the Partial Least Square (PLS) method (Kelly and Pruitt, 2013, 2015) to consolidate the information in the term structure into a single factor that matters most for the U.S. equity premium. We refer this factor to *the U.S. forward variance risk factor (FVF^{US})* and examine its predictive ability for stock market excess returns on the U.S. as well as 10 non-U.S. industrialized countries, including Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the United Kingdom.

The U.S. volatility risk factor positively predicts the monthly U.S. and international market excess returns from February 1996 to June 2019, with a significant regression slope estimate at the 10% level or better for all industrialized countries considered (except for Japan). The R^2 statistics produced by $\mathrm{FVF}^{\mathrm{US}}$ range from 0.45% (Japan) to 6.00% (Switzerland) during the whole sample, and are larger during NBER-dated recessions with an average R^2_{Rec} of 7.53% and lower during expansions with an average R^2_{Exp} of 1.28%, consistent with the counter-cyclical return predictability documented by the literature (Henkel, Martin, and Nardari, 2011). A pooled predictive regression with the slope homogeneity restriction for all countries (Rapach, Strauss, and Zhou, 2013) shows that on average, a one-standard-deviation increase in $\mathrm{FVF}^{\mathrm{US}}$ signals a 0.78% increase in the next-month international equity premium. This is economically sizable since most of the countries have a sample mean excess return below 0.5%. Therefore, our results imply that high U.S. volatility risk foreshadows future high international excess market returns.

We find that $\mathrm{FVF}^{\mathrm{US}}$ contains incremental information to the local financial and economic predictor variables, including the dividend yield, short rate, and term spread (Ang and

[2]Guo and Whitelaw (2006) find that using the option-implied variance rather than historical variance or GARCH-based variance forecasts improves the estimation efficiency and helps to recover the positive risk-return tradeoff relation.

Bekaert, 2007; Hjalmarsson, 2010), and its predictive ability remains robust after controlling for local volatility risk measured by the realized variance and option-implied VIX index. Besides, the predictability of $\mathrm{FVF}^{\mathrm{US}}$ cannot be explained by the existing U.S. variables that are found to predict international returns, including the U.S. variance risk premium (Bollerslev, Marrone, Xu, and Zhou, 2014; Bollerslev, Tauchen, and Zhou, 2009), lagged U.S. returns (Rapach et al., 2013), and the U.S. skewness innovations (Chen, Jiang, Xue, and Yao, 2019). Moreover, a battery of tests verifies that the predictive power of $\mathrm{FVF}^{\mathrm{US}}$ is robust to the way in which stock excess returns are measured (either in national currency or in U.S. dollar) and the choice of evaluation period.

The in-sample predictability analysis is subject to the look-ahead bias, and may potentially overestimate the degree of predictability in real-time (Welch and Goyal, 2008). We thus conduct an out-of-sample (OOS) analysis using the first 60 months of data as the initial training period (February 1996 to January 2001), following Welch and Goyal (2008). Over the evaluation period from February 2001 to June 2019, $\mathrm{FVF}^{\mathrm{US}}$ produces significantly positive OOS R^2 statistics (Campbell and Thompson, 2008) for the U.S. (2.17%) and for the other nine countries (except for Japan), with the highest being 4.37% for Switzerland. The OOS forecast encompassing test using on the statistic of Harvey, Leybourne, and Newbold (1998) further confirms $\mathrm{FVF}^{\mathrm{US}}$ contributes the incremental information to the existing U.S. and local predictors. Moreover, through a widely adopted asset allocation framework in the literature (Campbell and Thompson, 2008), we show that $\mathrm{FVF}^{\mathrm{US}}$ can generate substantial economic gains for both domestic investors who can invest in their own markets and a global investor who can invest across countries. The economic gains survive under a proportional transaction cost of 50 basis points.

We extend our study to emerging markets by considering 14 stock markets from Africa, Middle and South America, East and South Asia, and Europe. We observe prevailing positive relations between $\mathrm{FVF}^{\mathrm{US}}$ and excess returns on these markets. Nevertheless, the predictive power of $\mathrm{FVF}^{\mathrm{US}}$ for emerging markets is weak and nonsignificant compared to what we find in the developed markets. According to Bekaert and Harvey (1995) and Bekaert, Harvey, Lundblad, and Siegel (2011), emerging markets are largely segmented from developed markets, the U.S. in particular, and their market returns are predominantly driven by local risks. Market segmentation limits the impact of the U.S. volatility risk, and in turn, leads to the limited forecasting ability of FVF^{US}.

Why does the U.S. forward variance risk factor positively predict stock market returns of developed countries? We construct a volatility spillover network following Diebold and Yilmaz (2009, 2014) and Yang and Zhou (2017). We document the central role of the U.S. in the global volatility transmission network, that is, the U.S. has the greatest amount of volatility spillover to other countries. A subsample analysis reveals that the OOS predictability of FVF^{US} is stronger during periods with more pronounced spillover effect from the U.S. to other countries (such as the 2008 Global Financial Crisis) and during periods when the degree of global stock markets is higher. Intuitively, because international investors bear the volatility originated from the U.S., they require high compensation for their domestic stock markets. Our result is thus consistent with an international version of the ICAPM and underscores the unique role of the U.S. volatility as a source of global risk in shaping the international risk-return tradeoff.

We further explore the underlying economic mechanisms behind the predictive power of FVF^{US}. First, we find a significantly inverse relation between the U.S. forward variances and future U.S. economic conditions, measured by a group of economic indicators, such as the Chicago Fed National Activity Index and industrial production growth. Thus, the predictability of FVF^{US} for the U.S. market comes from its link with the expected economic condition. Given the leading role of the U.S. in the world economy, a downturn in the U.S. economy likely causes an adverse impact in global investment opportunities. We then show that the U.S. forward variance negatively predicts local economic growth and positively predicts local economic uncertainty proxied by the economic policy uncertainty index of Baker, Bloom, and Davis (2016). Thus, high U.S. forward variance predicts future low international economic growth and high uncertainty. Therefore, the tight link between U.S. forward variances and world economy enables FVF^{US} to track the equity premium variation caused by adverse shifts in the international investment opportunity set due to deteriorations in world economic conditions. Finally, we find that the forecasting ability of FVF^{US} does not originate from its ability to anticipate country-wide investor sentiment, thereby consistent with the risk-based explanation.

Our paper complements the international return predictability literature. Ang and Bekaert (2007) and Hjalmarsson (2010), among others, document the robust predictive power of a few domestic economic and financial variables. Additionally, a number of empirical studies elucidates the unique role of U.S. variables in predicting non-U.S. market returns (Bollerslev et al., 2014; Chen, Jiang, Liu, and Tu, 2017; Chen et al., 2019; Rapach et al., 2013). We contribute to the extant research by elaborating the cross-country impact of the U.S. volatility risk, through the lenses of the risk-return relation and the U.S. volatility spillover effect. Empirically, we show that a single factor extracted from the U.S. forward variance term structure provides increment predictive information to the local and U.S. variables identified in the literature. Combining FVF^{US} with existing predictors would reinforce the predictability of international stock markets and deepen our understanding of the international risk-return tradeoff.

Our paper also contributes to a recent strand of studies exploring the information content of U.S. forward variances. Bakshi et al. (2011) initiate the notion of forward variance and demonstrate that it can be synthesized approximately from a strip of European options. They find that the U.S. forward variances can predict the U.S market return and real activity in-sample. Luo and Zhang (2017) thereafter refine the methodology of Bakshi et al. (2011) by constructing model-free forward variances using option prices and show that they also predict U.S. market returns out-of-sample. Feunou et al. (2014) and Andreou et al. (2019) employ dimension reduction methods to study the predictive power of the term structure of U.S. (forward) variances for U.S. market returns and variance. These studies focus on the U.S. market only. This paper adds new empirical evidence to the literature by uncovering the central role of the U.S. volatility in determining the international risk-return tradeoff.

The rest of the paper proceeds as follows. Section 2 discusses the asset pricing implication of the market volatility risk and explains why the U.S volatility would matter for international markets. Section 3 introduces the data and the U.S. forward variance risk factor FVF^{US}. Section 4 presents empirical results and Section 5 explores the sources of the predictability. Section 6 presents several robustness checks. Section 7 concludes the paper.

2 Theoretical motivation

The aggregate market volatility plays an important role in asset pricing. In the seminal ICAPM of Merton (1973), the conditional market premium is a linear function of its conditional variance (the risk component) and its conditional covariance with the state variables that describe the investment opportunities (the hedge component),

$$E_t[r_{t+1}] = \gamma \cdot V_t + \theta \cdot Cov_t(r_{t+1}, X_{t+1}), \tag{1}$$

where r_{t+1} and X_{t+1} are the logarithm market excess return and state variables at $t+1$, respectively. V_t is time-t conditional market variance. $\gamma \equiv \frac{-J_{WW}W}{J_W} > 0$ is the representative investor's relative risk aversion coefficient and $J(W_t, X_t, t)$ is her derived utility function on wealth W_t where subscripts stand for partial derivatives.[3]

Eq.(1) implies a *partial* positive relation between the conditional market variance and the conditional market premium, a relation that has been tested extensively since Merton (1980). Despite of mixed evidence in the early literature, with improved measurements of volatility and refined econometric modelling of investors' conditional information, recent research tends to conclude that this relation does hold conditionally (Bali, 2008; Bali and Engle, 2010; Bali and Peng, 2006; Ghysels et al., 2005; Guo and Whitelaw, 2006; Ludvigson and Ng, 2007; Rossi and Timmermann, 2015). The relation between the market risk premium and the hedge component depends on $\theta \equiv \frac{-J_{WX}W}{J_W}$, whose sign is opposite to J_{WX}. If an increase in X_t signals an unfavorable shift in investment opportunities such that the representative investor reduces consumption and increase precautionary savings, her marginal value of wealth would rise, implying $J_{WX} > 0$ and $\theta < 0$. Conversely, θ is positive.

It is well documented that the stock market return volatility is time-varying, inducing stochastic changes in investment opportunities. An increase in market volatility reduces the overall diversification and worsens the risk-return tradeoff. In addition, heightened market volatility often accompanies with market downturns (e.g., 2008 Global Financial Crisis). Thus, many studies argue that risk-averse investors want to hedge the market volatility risk, rendering market volatility itself a state variable of special hedging concern (e.g., Ang, Hodrick, Xing, and Zhang, 2006; Maio and Santa-Clara, 2012). Chen (2002) and Campbell, Giglio, Polk, and Turley (2018) formally develop discrete-time ICAPMs with time-varying volatility that extend the homoskedastic ICAPM of Campbell (1993). An increase in market volatility represents a deterioration in investment opportunities in their models. An asset

[3] Nonsatiation of utility implies $J_W > 0$ and risk averse implies $J_{WW} < 0$.

that has positive covariance with a state variable that positively forecasts future market volatility earns a lower equilibrium risk premium because investors demand insurance against market volatility risk and such asset precisely constitutes a volatility hedge. Therefore, the market volatility should be a negatively priced state variable, i.e., $\theta < 0$.[4]

The ICAPM serves as the foundation for our study to investigate the role of U.S. volatility for the equity premium. The first term in the right hand side of Eq.(1) implies a conditional positive relation between the market volatility and expected market return, ceteris paribus. Besides, the empirical studies of the ICAPM shows that the market volatility commands a negative premium in the U.S. stock market.[5] This, combined with the stylized fact that the conditional correlation between stock returns and market volatility is negative[6] implies that $\theta \cdot Cov_t(r_{t+1}, V_{t+1})$ should also be positive in market volatility. In sum, the U.S. volatility should be positively related to future U.S. market returns. This implication, however, does not explain why U.S volatility matters for international markets. We then analyze the cross-country role of U.S volatility from the perspective of international investors whose investment opportunities comprise both local and U.S. markets.

Over the past three decades, trade and financial liberalizations considerably increase the financial integration of global equity markets (Bekaert et al., 2011; Bekaert, Hodrick, and Zhang, 2009; Chen and Zhang, 1997). It is conceivable that equity volatility risk is priced globally, that is, the rewards to equity volatility risk exposure are common for integrated stock markets. Given the giant size of U.S. economy, as well as the tight connection maintained by the U.S. with other industrialized countries through bilateral trades and foreign direct investments, the U.S. volatility can transmit to other connected markets and constitutes a source of global risk (Bekaert, Harvey, and Ng, 2005; Sarno, Schneider, and Wagner, 2012). A shock to it, such as the volatility spike in October 2008 caused by the bankruptcy of Lehman Brothers, would affect investors both in and outside the U.S. and represents a deterioration in the global investment opportunities. Indeed, there is much evidence of the spillover of the U.S. volatility to the European Union and Japan, and its spillover intensity

[4]See also the long-run risk model by Bansal, Kiku, Shaliastovich, and Yaron (2014).

[5]The negative risk premium of the U.S. volatility is a robust finding of empirical studies that use both equity index option prices and stock returns (Ang et al., 2006; Bakshi and Kapadia, 2003; Cremers, Halling, and Weinbaum, 2015).

[6]This phenomenon is often called as "leverage effect" (Black, 1976) or "volatility feedback effect" (e.g., Guo and Whitelaw, 2006).

has been intensified since 2008 (Baele, 2005; Hamao et al., 1990; Yang and Zhou, 2017). Buncic and Gisler (2016) also show that incorporating the information of U.S. volatility considerably improves the forecast performance of 17 international equity markets' volatility. Accord to an international version of ICAPM, investors would require higher compensations for holding the local stock markets when facing heightened U.S. equity volatility. This implies a positive relation between the U.S. volatility and future international stock returns, and this relation should hold in the presence of local volatility risk. We test this prediction in the following sections.

3 Data and the U.S. Forward Variance Risk Factor

In this section, we describe the data of international stock market returns and the S&P 500 options used to construct the term structure of forward variances that measure the conditional U.S. volatility risk. Next, we illustrate the econometric method for constructing the U.S. forward variance risk factor.

3.1 International Stock Market Return Data

We collect the stock market indices of the U.S. and 10 non-U.S. industrialized countries, including Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the United Kingdom.[7] The selection of countries and market indices follows Rapach et al. (2013). We calculate the logarithm market return (including dividends) in excess of the risk-free rate, where the excess returns are measured in the national currency, following Solnik (1993), Ang and Bekaert (2007), and Hjalmarsson (2010), among others. As pointed out by Solnik (1993), using national currency returns sidesteps the difficulty of modelling the exchange rate risk premia, and allows us to concentrate on the equity risk premia. All data are from the Global Financial Data (GFD) and span monthly from January 1996 to June 2019. The stock returns are derived from GFD's value-weighted total return indices database, and the risk-free rates are proxied by domestic three-month Treasury bill

[7] We extend our study to additional 11 developed markets, including Austria, Belgium, Denmark, Finland, Israel, New Zealand, Norway, Portugal, Spain, Hong Kong, and Singapore. The results are quantitatively similar and are available upon request.

rates. Table A.1 provides detailed descriptions of the data.

Panel A of Table I reports the summary statistics of the monthly logarithm stock market excess returns. There are considerable heterogeneity among the 11 countries. The average excess returns range from 0.11% (Japan) to 0.68% (Sweden), and the standard deviations vary from 3.66% (Australia) to 5.976% (Italy). All the country returns are negative skewed and leptokurtic with the return skewness ranging from -1.31 (Canada) to -0.10 (Italy). A few countries, such as Canada and Switzerland, exhibit notably positive return autocorrelations. The correlations of excess returns of the 11 countries shown in Panel B of Table I suggest that these stock markets exhibit strong return comovements.

[**Insert Table I here**]

3.2 Option-Implied U.S. Forward Variances

To measure the conditional U.S. volatility risk, we construct the model-free implied variance, or the VIX index, from the S&P 500 option prices using the methodology of the CBOE (CBOE, 2009). The theoretical foundation behind the VIX index is that the risk-neutral expected return variations of the S&P 500 index from the current time t to a future date T can be replicated by a strip of options with the same expiration date,

$$E_t^{\mathbb{Q}}\left[\int_t^{t+\tau}\left(\frac{dS_u}{S_u}\right)^2\right]=\frac{2}{B_{t,\tau}}\left[\int_0^{F_{t,\tau}}\frac{P_{t,\tau}(K)}{K^2}dK+\int_{F_{t,\tau}}^{\infty}\frac{C_{t,\tau}(K)}{K^2}dK\right],\quad \tau\equiv T-t, \tag{2}$$

where S_t is time-t spot index price, $E_t^{\mathbb{Q}}$ is the conditional expectation under the risk-neutral probability measure $\mathbb{Q}$, $B_{t,\tau}$ is the price of a risk-free discount bond matured at T, $F_{t,\tau}$ is the forward price of maturity τ, and $P_{t,\tau}(K)$ and $C_{t,\tau}(K)$ denote the prices of European put and call options on the index with strike K and maturity τ, respectively. The VIX index, denoted as $\text{VIX}_{t,\tau}$, is defined as the square root of the expectation in Eq. (2) divided by τ. The CBOE uses this methodology to calculate their 30-day VIX index, which is widely known as the "fear index" by market participants.[8] It is worth mentioning that the VIX index is "model-free" in that it does not require any specific asset pricing model.[9]

[8] `https://www.cboe.com/tradable_products/vix/`.

[9] Britten-Jones and Neuberger (2000) derive this result under the assumption that the index follows a diffusion process. Jiang and Tian (2005) and Carr and Wu (2009) show that this expression also holds

Empirically, the VIX has a forward-looking advantage relative to the volatility estimated from historical return data (Busch et al., 2011; Jiang and Tian, 2005). More importantly, we can construct a term structure of VIX indices with different expiration dates according to Eq. (2), which should be informative for identifying the true yet unobservable volatility risk factor. We transform these VIX indices into "model-free" forward variances. Conceptually, forward variances are similar to forward rates and measure the risk-neutral expected return variations over non-overlapped time intervals, which helps to separate the pieces of information in the VIX indices (Andreou et al., 2019; Bakshi et al., 2011; Luo and Zhang, 2017). Formally, a time-t model-free forward variance from $t+\tau_i$ to $t+\tau_{i+1}$ is given by,

$$\mathrm{FV}_{i,t} \equiv E_t^{\mathbb{Q}}\left[\int_{t+\tau_i}^{t+\tau_{i+1}} \left(\frac{dS_u}{S_u}\right)^2\right] = \tau_{i+1}\mathrm{VIX}^2_{t,\tau_{i+1}} - \tau_i \mathrm{VIX}^2_{t,\tau_i}, \quad \tau_i < \tau_{i+1}. \tag{3}$$

To calculate the U.S. forward variances, we collect the S&P 500 option (SPX) price data from OptionMetrics. We first apply some common filters to remove recording errors and reduce the effect of option illiquidity. Specifically, we delete observations that violate non-arbitrage bounds, have zero bid quotes, or have maturities less than a week. In addition, we only keep standard SPX options expiring on the third Friday (or the Saturday thereafter) of each month.[10] Next, we compute the VIX indices for all available expiration dates using out-of-money call and put options, upon which we construct a set of constant-maturity VIX indices via linear interpolation (CBOE, 2009). Finally, we obtain a term structure of constant-maturity forward variances according to Eq.(3), covering the index return variations over intervals $[t+3m, t+6m]$, $[t+6m, t+9m]$, $[t+9m, t+12m]$, and $[t+12m, t+18m]$. We denote them as FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m}, respectively.

Panel B of Table I reports the descriptive statistics of the monthly constant-maturity forward variances by using data on the penultimate trading day of each month.[11] The sample spans from January 1996 to June 2019. The mean of the forward variances increases from 1.31 to 2.80 as the term structure moves from the short to the long end. All the

approximately with high accuracy where the index process contains jumps. Carr and Madan (2001) and Kozhan, Neuberger, and Schneider (2013) show that this expression is also the fixed leg of a variance swap that delivers the floating leg of the realized index return variations over the time interval $[t, T]$.

[10] To mitigate truncation errors due to the limited range of available strikes when computing the integrations in Eq.(2) numerically, we extrapolate outside this range following Jiang and Tian (2005).

[11] The closing time of U.S. stock market is the latest among the 11 markets. This one-day lag rule is to avoid the look-ahead bias in the following predictive analyses.

forward variances are positively skewed and leptokurtic and exhibit strong persistence. The pairwise correlation coefficients shown in Panel C range from 0.91 to 0.97, suggesting that they collectively capture a common aspect about the U.S. volatility risk.

[**Insert Fig 1 here**]

To provide further perspectives on the forward variances, we plot their dynamics in Figure 1. The shaded area denotes National Bureau of Economic Research (NBER) recessions. The forward variances are high during recessions and turbulent periods (e.g., the 1997 Asian crisis and the 2010-2011 European sovereign debt crisis) and peak at the 2008 Global Financial Crisis. In particular, they raise rapidly in the beginning of 2007. Subsequently, we observe the U.S. sub-prime mortgage debt crisis and the decline of the U.S. market, which transmits to other countries rapidly and eventually evolves into an unprecedented global market downturn. Thus, an increase in the forward variances signals not only heightened U.S. volatility risk, but also a lift in global volatility. From this perspective, they collectively represent a source of global risk that matters for international markets.

3.3 U.S. Forward Variance Risk Factor

In this paper, we consider each U.S. forward variance as a proxy for the true yet unobserved U.S. volatility risk, V, that affects both the U.S. and international equity premia. We extract their common component to provide a better measure of V.

Following the discussion in Section 2, we assume that the one-period-ahead U.S. equity premium is a linear function of the conditional U.S. volatility risk V_t:

$$E_t[r_{t+1}^{\mathrm{US}}] = \alpha + \beta V_t, \tag{4}$$

where r_{t+1}^{US} is the logarithm U.S. market excess return. Since the realized excess return can be decomposed into its conditional expectation plus a shock, we can write

$$r_{t+1}^{\mathrm{US}} = \alpha + \beta V_t + \epsilon_{t+1}, \tag{5}$$

where ϵ_{t+1} has a zero mean and is unrelated to V_t.

Let $\mathrm{FV}_t = (\mathrm{FV}_{1,t}, \mathrm{FV}_{2,t}, ..., \mathrm{FV}_{N,t})'$ denote the vector of constant-maturity U.S. forward variances. We assume a linear factor model for $FV_{i,t}$ that follows

$$\mathrm{FV}_{i,t} = \theta_{0,i} + \theta_{1,i} V_t + \theta_{2,i} \varphi_t + \eta_{i,t}, \quad i = 1, ..., N, \tag{6}$$

where $\mathrm{FV}_{i,t}$ is affected by both V_t and φ_t, φ_t is the common component of all forward variances that is irrelevant to the U.S. equity premium (such as a measurement error), $\theta_{1,i}$ measures the sensitivity of $\mathrm{FV}_{i,t}$ to V_t, and $\eta_{i,t}$ is the idiosyncratic shock to $\mathrm{FV}_{i,t}$ exclusively. The linear factor structure of forward variances is inline with a broad class of affine models, in which the conditional mean and variance of asset logarithm returns at different time horizons are affine functions of a set of common state variables.[12] In our context, the state variable is the conditional U.S. volatility risk V_t, and both the term structure of U.S. forward variances and the conditional U.S. equity premium are affine functions of V_t (e.g., Andreou et al., 2019; Feunou et al., 2014).

Partial Least Squares

Since each forward variance contains certain information about V_t, we can run the standard ordinary least square (OLS) regression to test the relation between the U.S. forward variances and U.S. and international stock returns. However, given the strong correlations among the forward variances, the multi-collinearity problem would obscure the risk-return relation. In addition, the OLS regression is not guaranteed to separate V_t from the irrelevant component φ_t and thus can produce less efficient forecasts. Therefore, we utilize the PLS method, pioneered by Wold (1966) and further advanced by Kelly and Pruitt (2013, 2015), to extract V_t from the term structure of forward variances. Specifically, PLS is a target-driven dimension reduction method that extracts the common factor from the set of U.S. forward variances $\{FV_{i,t}\}$ by exploiting the factor structures of Eq. (4-6). The extracted factor is a linear combination of the forward variances where the weight on each $FV_{i,t}$ is based on its covariance with future market excess return.

[12] Affine models serve as the bedrock for pricing derivatives, and are also popular in equilibrium asset pricing studies, such as the affine long-run risk models with Epstein-Zin-Weil preferences (Bansal and Yaron, 2004; Bollerslev et al., 2009; Eraker, 2008). See the systematic treatment of affine models by Duffie, Pan, and Singleton (2000) in continuous time and by Darolles, Gourieroux, and Jasiak (2006) in discrete time.

The PLS factor can be estimated through a two-stage OLS regression. In the first stage, we run N time-series regressions separately for each forward variance $\mathrm{FV}_{i,t}$ on the U.S. market excess return r_{t+1}^{US},

$$\mathrm{FV}_{i,t} = \delta_{0,i} + \delta_i r_{t+1}^{\mathrm{US}} + \xi_{i,t}, \quad \text{for } i = 1, ..., N, \tag{7}$$

where δ_i is the loading that measures the sensitivity of $\mathrm{FV}_{i,t}$ to r_{t+1}^{US}.

In the second stage, we run a cross-sectional regression of FV_t on the estimated exposure $\hat{\delta} \equiv (\hat{\delta}_1, ..., \hat{\delta}_N)'$, for each period t,

$$\mathrm{FV}_t = \theta_t + \hat{\delta}\, \mathrm{FVF}^{\mathrm{US}} + \nu_t, \quad \text{for } t = 1, ..., T, \tag{8}$$

where the first-stage loading estimate $\hat{\delta}$ serves as the independent variables to explain the cross sectional variation of FV_t and the regression slope in Eq. (8) is the PLS factor. In particular, we refer to the PLS factor estimated from the set of U.S. forward variances, FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m}, as the U.S. forward variance risk factor, $\mathrm{FVF}^{\mathrm{US}}$.

Intuitively, a higher value of the loading δ_i indicates that $\mathrm{FV}_{i,t}$ has a higher exposure to V_t instrumented by r_{t+1}, and thus carries a larger amount of information about V_t. As proved by Kelly and Pruitt (2015), PLS utilizes this feature precisely such that the extracted factor $\mathrm{FVF}^{\mathrm{US}}$ efficiently estimates the true volatility risk V_t from individual forward variances and at the same time filters out the irrelevant common and idiosyncratic noise components φ_t and $\xi_{i,t}$. A number of recent empirical studies demonstrate that PLS is an efficient method for obtaining the latent common factor from individual predictive variables (Huang, Jiang, Tu, and Zhou, 2015; Kelly and Pruitt, 2013).

Using the PLS procedure outline above, we obtain the U.S. forward variance factor $\mathrm{FVF}^{\mathrm{US}}$ over the full sample, which is given by

$$\mathrm{FVF}_t^{\mathrm{US}} = 26\mathrm{FV}_{3m6m,t} + 13\mathrm{FV}_{6m9m,t} - 95\mathrm{FV}_{9m12m,t} + 45\mathrm{FV}_{12m18m,t}. \tag{9}$$

Accordingly, we interpret $\mathrm{FVF}^{\mathrm{US}}$ as a slope-curvature factor because it captures the slope of the term structure of the forward variances and its loading also has a U-shape on forward variances with maturity longer than six months. Consistent with this interpretation, we note that FVF^{US} has the correlations of 0.07, 0.74, and -0.66 with the first, second, and third principal components, respectively.[13]

4 Empirical results

In this section, we examine the predictive ability of the U.S. forward variance risk factor FVF^{US} for the U.S. and 10 non-U.S. markets. We start with in-sample predictive analyses and move to out-of-sample tests. Finally, we quantify the economic value of the predictability of FVF^{US} through an asset allocation practice.

4.1 Baseline predictive regression

Our baseline predictive regression is

$$r_{i,t+1} = \alpha_i + \beta_i \,\text{FVF}_t^{\text{US}} + \varepsilon_{i,t+1}, \tag{10}$$

where $r_{i,t+1}$ is the logarithm market excess return of country i at month $t+1$ and FVF_t^{US} is the U.S. forward variance risk factor extracted from the term structure of U.S. forward variance. We use the U.S. forward variances in the penultimate trading day of each month to avoid a look-ahead bias. The sample spans from February 1996 to June 2019. To ease interpretation, FVF_t^{US} is standardized to have zero mean and unit variance, so that its coefficient can be interpreted as the effect of a one standard deviation increase in the U.S. forward variance factor on the country i's one-month ahead return. We make the statistical inference for β_i based on the t-statistic of Kelly and Pruitt (2015). The null hypothesis is $\beta_i = 0$ that FVF_t^{US} has no predictability, against the alternative hypothesis that β_i is different from zero.

[**Insert Table II here**]

As shown in Table II, FVF^{US} positively predicts the future excess stock market returns on the 11 industrialized countries. High U.S. volatility risk forecasts future high international returns, consistent with the risk-return relation implied by the ICAPM. The slope

[13] This result is different from that of Andreou et al. (2019) who also apply PLS to extract the common factor from the term structure of U.S. forward variances. However, their forward term structure does not involve the forward variance FV_{12m18m} as we do.

estimates of FVF^{US} range from 0.34% (Japan) to 1.06% (Switzerland), all of which are significant at the 10% level or better, with the exception of Japan.[14] This suggests that FVF^{US} provides certain amount of information for forecasting the future international equity premium. The magnitude of the slope estimates is also economically significant. For instance, a one-standard-deviation increase in FVF^{US} indicates a rise in the monthly equity premium of 1.02% , 1.04%, and 0.68% for France, Germany, and the U.S., respectively, considerably larger than the corresponding country's average excess returns (0.52% for France, 0.43% for Germany, and 0.52% for the U.S., see Table I).

According to the fourth column of Table II, the R^2 statistics produced by FVF^{US} are generally greater than 2%, with the highest being 6% for Switzerland. These R^2 values signal an economically sizable degree of return predictability of FVF^{US}. As argued by Campbell and Thompson (2008), even a small monthly R^2, such as 0.5% in the U.S. data, can translate into a more than 30% proportional increase in the portfolio expected return to a mean-variance investor who can employ the predictive regression forecast.

The extant literature documents that the degree of stock return predictability of G7 countries varies over business cycles and the predictability concentrates in periods with economic recessions (Henkel et al., 2011; Rapach, Strauss, and Zhou, 2010). To investigate the predictive ability of FVF^{US} under different economic phases, we follow Henkel et al. (2011) to split the sample into expansions and recessions based on the NBER-dated business cycle indicator, and compute the R^2 for each subsample,

$$R_{i,c}^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c(\varepsilon_{i,t})^2}{\sum_{t=1}^{T} I_t^c(r_{i,t} - \bar{r}_i)^2}, \quad c = \text{Rec} \quad \text{or} \quad \text{Exp}, \tag{11}$$

where I_t^{Rec} (I_t^{Exp}) equals to one whenever the U.S. economy is in NBER recession (expansion) month t and zero otherwise, $\varepsilon_{i,t}$ denotes the fitted residual from regression equation Eq.(10), and $\bar{r}_i$ is the full-sample mean of r_i. Note that unlike the full-sample R^2 statistic, R^2_{Exp} and R^2_{Rec} can be negative.

The last two columns in Table II reveal that the return predictability is more pronounced during recessions than during expansions for FVF^{US}. The average R^2_{Rec} value for the 11 coun-

[14] The Japanese stock market is difficult to predict by conventional predictor variables, such as bond yields and valuation ratios. See Aono and Iwaisako (2011) and the references therein.

tries is 7.53% (not tabulated), more than five times larger than the average R^2_{Exp} of 1.28% (not tabulated). Therefore, the predictive power of the U.S. forward variance risk factor displays a counter-cyclical pattern. This is in line with the model in Section 2 that the heightened global risk, approximated by the U.S. volatility risk, drives up the international equity premium during recessions, thereby leading to counter-cyclical predictability. Moreover, as presented by the optimal attention model of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), fund managers focus more on idiosyncratic shocks during expansions but more on aggregate shocks during recessions. Since the U.S. volatility risk is approximate for the aggregate risk that affects the global financial markets, international investors would place more attention on it during recessions, giving rise to counter-cyclical predictability for FVF^{US}.

In addition, we follow Ang and Bekaert (2007), Hjalmarsson (2010), and Rapach et al. (2013) to estimate a pooled regression of Eq. (10) by imposing the slope homogeneity restriction $\beta_i = \bar{\beta}$ for all country i but allowing for country-specific intercepts. As argued by Rapach et al. (2013), although pooling may induce a biased slope estimate, it can improve estimation efficiency by reducing mean squared error. Furthermore, the pooled slope estimate can be interpreted as the average relation between the U.S. forward variance risk factor and future international stock returns. The last row of Table II shows that the pooled estimate of β is 0.78%, which is sizable and significant at the 1% level. Accordingly, on average, a one-standard-deviation increase in FVF^{US} corresponds to a 0.78% increase in the next-month international excess returns.

4.2 Multivariate predictive regression

In this subsection, we study whether the U.S. forward variance risk factor contains any incremental information to existing predictors in literature.

Controlling for local financial and economic conditions

We consider a set of local financial and economic variables that can predict local stock market returns, including the nominal risk-free rate proxied by the three-month T-bill rate (TBL), the aggregate stock market dividend yield (DY), and the term spread which is the difference between the 10-year government bond yield and the three-month T-bill rate (TMS) (Ang and Bekaert, 2007; Hjalmarsson, 2010; Rapach et al., 2013). The data are from the Global Finance Data. We also control for the January effect on the stock return predictability by including a dummy variable equal to one if the return is in January and zero otherwise (Jan), as in Solnik (1993) and Chen et al. (2019).

[**Insert Table III here**]

The predictive regression controlling for local financial and economic variables is,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{TBL}_{i,t} + \beta_{i,3}\mathrm{DY}_{i,t} + \beta_{i,4}\mathrm{TMS}_{i,t} + \beta_{i,5}\mathrm{Jan}_{t+1} + \varepsilon_{i,t+1}, \quad (12)$$

where $\mathrm{TBL}_{i,t}$ is the three-month T-bill rate of country i at time t, $\mathrm{DY}_{i,t}$ is the aggregate stock market dividend yield of country i at time t, $\mathrm{TMS}_{i,t}$ is the term spread of country i at time t, and Jan_{t+1} is the January effect dummy variable. All predictors are standardized to have a zero mean and unit variance, except for the January dummy.

Panel A of Table III reports the estimation results of regression (12). After controlling for local financial and economic variables, $\mathrm{FVF}^{\mathrm{US}}$ continues to positively predict future excess returns on the 11 markets, with 10 slope estimates that are significant at least at the 10% level. The values of regression R^2 are substantially increased, ranging from 2.17% (Canada) to 10.42% (Switzerland), more than double the values shown in Table II. This indicates that $\mathrm{FVF}^{\mathrm{US}}$ and the local economic variables contribute unique information regarding on future stock returns. Turning to the local economic variables, we find the dividend yield and the January dummy insignificant. Nonetheless, the T-bill rate and term spread exhibit certain predictive power, with significant slope estimates for five and four markets, respectively. Similarly, we estimate a pooled version of regression (12) in the last row of Panel A. The pooled OLS estimate of $\mathrm{FVF}^{\mathrm{US}}$ is significant at 1% level, and is identical with the pooled estimate in the baseline regression (10), reaffirming that $\mathrm{FVF}^{\mathrm{US}}$ contains distinct forecasting information from those in local financial and economic predictors. Among the other four variables, only TMS has a significant pooled slope estimate but in a much smaller size of 0.38%.

Controlling for local volatility risk

To examine whether the predictability for $\mathrm{FVF}^{\mathrm{US}}$ can be explained by local market risk, we control for the local stock market variance. We use realized variance computed as the sum of the squared daily returns within a month as the proxy for market variance (SVAR). Besides, we consider an alternative proxy for the local volatility risk using the local VIX index, while the results are basically similar which can be found in the Internet Appendix. The predictive regression augmented with the local volaility risk is,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{SVAR}_{i,t} + \varepsilon_{i,t+1}, \tag{13}$$

where $\mathrm{SVAR}_{i,t}$ is the realized market variance of country i at time t, which has a mean of zero and unit variance.

Panel B of Table III reports the estimation results of regression (13). Incorporating local risk measure SVAR into the regression does not change the size or significance of the slope estimates corresponding to $\mathrm{FVF}^{\mathrm{US}}$, suggesting that local volatility risk cannot explain the predictive power of the U.S. forward variance risk. As a comparison, local SVARs evince weak predictive ability that is significant only for three out of the 11 countries (Australia, Canada, and the U.S.). Therefore, the above results underscore the primary role played by the U.S. market risk in driving the variation of the international equity market risk premium, consistent with Londono (2015).

Controlling for alternative U.S. predictors

The literature has uncovered a series of U.S. variables that can significantly predict international stock market returns, including the lagged U.S. stock market return (Rapach et al., 2013), the U.S. variance risk premium (VRP) (Bollerslev et al., 2014, 2009), and innovation of the U.S. stock market skewness (Chen et al., 2019). We thus control for these U.S. predictive variables to address the concern that the predictive ability of $\mathrm{FVF}^{\mathrm{US}}$ may stem from its correlations with existing U.S. predictors. The innovation of U.S. skewness is measured by the monthly difference of the CBOE option-implied skewness index. The U.S. VRP is calculated as the difference between the squared VIX and the realized variance of the month.[15] The predictive regression augmented with existing U.S. predictors is,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}^{\mathrm{US}}_{i,t} + \beta_{i,2}\mathrm{SKEW}^{\mathrm{US}}_{t} + \beta_{i,3}\mathrm{VRP}^{\mathrm{US}}_{t} + \beta_{i,4} r_{\mathrm{US},t} + \varepsilon_{i,t+1}, \tag{14}$$

where SKEW^{US}_{t} is the monthly innovation of the U.S. stock market skewness, VRP^{US}_{t} is the U.S. VRP, and $r_{\mathrm{US},t}$ is the lagged excess U.S. market return. All predictors have a mean of zero and unit variance.

Panel C of Table III reports the estimation results of regression (14). In general, controlling for alternative U.S. predictors does not affect the predictive power of $\mathrm{FVF}^{\mathrm{US}}$ much. The slope estimates of $\mathrm{FVF}^{\mathrm{US}}$ remain positive and are significant at least at the 10% level for eight countries. Compared to the results in TableII, $\mathrm{FVF}^{\mathrm{US}}$ loses its significance for two countries (Australia and Canada), in which the U.S. VRP and lagged U.S. market return become the dominant predictors, respectively. The pooled estimation results in the last row show that $\mathrm{FVF}^{\mathrm{US}}$ on average has the largest and most significant slope estimate among all U.S. predictors, indicating that the U.S. forward variance risk factor has a quantitatively more important impact on international stock returns relative to the other U.S. variables. Hence, $\mathrm{FVF}^{\mathrm{US}}$ provides a substantial amount of incremental information about the international equity premium variation to the extant U.S. predictors.

Overall, the results in Table III demonstrate that the U.S. forward variance risk factor displays a strong predictive power for international stock market returns that cannot be fully explained by the local economic variables, local volatility risk, and the existing U.S. predictors.

4.3 Out-of-sample tests

Welch and Goyal (2008) have shown that many well-recognized predictors fail to consistently predict the equity premium in OOS forecasting, and in fact, most of them are inferior to the simple historical average forecast in term of predictive accuracy, especially over the recent decades. In this subsection, we perform OOS predictive analyses for the U.S. forward variance risk factor. Since OOS forecasting avoids the look-ahead bias and over-fitting prob-

[15] We thank Hao Zhou for making the data available at his website `https://sites.google.com/site/haozhouspersonalhomepage/`.

lems involved with the in-sample analysis, it helps to detect the stability and reliability of the predictive power of FVF^{US} in real time.

Following Welch and Goyal (2008), we generate OOS return forecasts by estimating the regression coefficients of Eq. (10) recursively using only the information available at the time when the forecasts are made. We use the first 60 months of data as the initial training period (February 1996 to January 2001), so the first return forecast is made for February 2001 and the OOS evaluation period ranges from February 2001 to June 2019, with a total of 221 observation points for each country. The choice of the initial training window of 60 months is to make a balance between an adequate amount of start-up observations for parameter estimation and a sufficiently long OOS period for evaluating the forecasting performance.

We rely on the OOS R^2 statistic (R^2_{OS}) of Campbell and Thompson (2008) to assess the OOS predictive performance, which is calculated as

$$R^2_{OS} = 1 - \frac{\sum_{t=H}^{T-1}(r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{t=H}^{T-1}(r_{i,t+1} - \bar{r}_{i,t+1})^2} = 1 - \frac{\text{MSFE}_{Model\ i}}{\text{MSFE}_{Bench}}, \tag{15}$$

where H is the length of the initial training period (60 in our case), T is the total sample size, $r_{i,t+1}$ denotes the realized excess log market return of country i at month $t+1$, $\hat{r}_{i,t+1}$ is the return forecast formed based on predictive model i, and $\bar{r}_{i,t+1} = \frac{1}{t}\sum_{s=1}^{t} r_{i,s}$ is the historical average benchmark forecast. Evidently, a positive R^2_{OS} value indicates that the predictive model i produces a lower mean squared forecast error (MSFE) than the historical average benchmark does. In other words, the R^2_{OS} statistic measures the statistical predictive accuracy of the regression forecast generated by model i relative to the benchmark. We employ the MSFE-adjusted statistic of Clark and West (2007) to test the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative hypothesis $R^2_{OS} \geq 0$.

[**Insert Table IV here**]

Panel A of Table IV reports the R^2_{OS} statistics of FVF^{US} over the full OOS sample period as well as during periods of recession ($R^2_{OS,Rec}$) and expansion ($R^2_{OS,Exp}$).[16] The second

[16] The R^2_{OS} values during periods of recession and expansion are calculated as

$$R^2_{OS,c} = 1 - \frac{\sum_{t=H}^{T-1} I^c_{t+1}(r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{t=H}^{T-1} I^c_{t+1}(r_{t+1} - \bar{r}_{i,t+1})^2}, \quad c = \text{Rec or Exp},$$

column shows that all the R^2_{OS} statistics produced by $\mathrm{FVF}^{\mathrm{US}}$ are positive and statistical significant except for Japan. This implies that $\mathrm{FVF}^{\mathrm{US}}$ delivers a significantly lower MSFE than that of the historical average benchmark for almost all countries considered. Consistent with the in-sample R^2 results, $\mathrm{FVF}^{\mathrm{US}}$ exhibits the greatest predictive ability for Switzerland with an R^2_{OS} of 4.37% that is significant at the 1% level, then followed by France with an R^2_{OS} of 3.59%. Also note that $\mathrm{FVF}^{\mathrm{US}}$ appears to be a strong predictor for the U.S. equity premium, with an R^2_{OS} of 2.17% that is significant at the 5% level. Accordingly, $\mathrm{FVF}^{\mathrm{US}}$ outperforms a host of conventional predictors in forecasting U.S. stock market returns.

According to the third and fourth columns of IV, $\mathrm{FVF}^{\mathrm{US}}$ outperforms the historical average forecast during both recession and expansion, as indicated by the positive values of $R^2_{OS,Rec}$ and $R^2_{OS,Exp}$ for most of the countries. Nonetheless, the $R^2_{OS,Rec}$ values greatly exceed the $R^2_{OS,Exp}$ counterparts except for Japan. For instance, the $R^2_{OS,Rec}$ value for Switzerland is 10.23%, nearly five times higher than the corresponding $R^2_{OS,Exp}$ value of 2.10%. This reiterates the notion that the predictive power of the U.S. forward variance risk factor is counter-cyclical and concentrates around periods with economic recessions

Furthermore, we compare the information content of $\mathrm{FVF}^{\mathrm{US}}$ to other competing predictive models through the OOS forecast encompassing test. Specifically, we form an optimal convex combination forecast for country i based on the forecasts by $\mathrm{FVF}^{\mathrm{US}}$ and the competing predictive model of interest,

$$\hat{r}^{*}_{i,t+1} = (1-\lambda)\hat{r}^{\mathrm{Comp}}_{i,t+1} + \lambda \hat{r}^{\mathrm{FVF}^{\mathrm{US}}}_{i,t+1}, \quad 0 \leq \lambda \leq 1, \tag{16}$$

where $\hat{r}^{*}_{i,t+1}$ denotes the optimal return forecast for country i and $\hat{r}^{\mathrm{FVF}^{\mathrm{US}}}_{i,t+1}$ ($\hat{r}^{\mathrm{Comp}}_{i,t+1}$) is the return forecast for country i generated by $\mathrm{FVF}^{\mathrm{US}}$ (the competing model). A positive λ indicates that $\mathrm{FVF}^{\mathrm{US}}$ contributes incremental forecasting information to the competing model, while a trivial λ indicates that $\mathrm{FVF}^{\mathrm{US}}$ rarely provides any additional information in the optimal composite forecast, thereby being encompassed by the competing model. We gauge the significance of λ based on the HLN statistic of Harvey et al. (1998), which tests the null hypothesis $\lambda = 0$ against the one-sided alternative $\lambda \geq 0$.

where I^{Rec}_{t+1} (I^{Exp}_{t+1}) equals one whenever the economy is in an NBER-dated recession (expansion) in month $t+1$, and zero otherwise.

Panel B of Table IV reports p-values for the HLN statistic applied to the OOS forecasts. The fifth and sixth columns consider the competing models that are constituted of the local financial and economic variables in regression (12) (local Econ) and the local volatility risk measure in regression (13) (local SVAR), respectively. We can reject the null hypothesis that the local financial and economic variables forecast encompasses the FVF^{US} forecast at the 1% level for all countries but Italy. Similar results hold for the case in which we use local SVAR as the competing predictive variable. Turning to the last column, we can significantly reject the null hypothesis that FVF^{US} is encompassed by a collection of alternative U.S. predictors (with the exception of Australia). Thus, we can conclude that the U.S. forward variance risk factor provides additional information to the existing predictors that helps to explain variations in the international equity premium.

In sum, the results in Table IV confirm the stability of the forecasting ability of FVF^{US} in OOS prediction and complement the findings derived from the in-sample analysis.

4.4 Asset allocation analysis

In this subsection, we assess the economic value of the predictability of FVF^{US} from an asset allocation perspective. Following Campbell and Thompson (2008) and Rapach et al. (2010), among others, we consider a mean-variance investor who uses OOS excess return forecasts for a specific country to guide asset allocation decisions across risky assets (stock market index in our case) and risk-free bonds. We assume that the investor rebalances the portfolio at the end of each month, and the optimal portfolio weight on the stock market index is,

$$w_{i,t} = \frac{\hat{R}^e_{i,t+1}}{\gamma \hat{\sigma}^2_{i,t+1}}, \tag{17}$$

where γ is the risk aversion coefficient, $\hat{R}^e_{i,t+1}$ is the stock excess return forecast for country i, and $\hat{\sigma}^2_{i,t+1}$ is the return variance forecast. We follow Campbell and Thompson (2008) to use the sample variance of excess returns over the past five years as the variance estimate of the future excess returns, and we impose a short-sale constraint as well as a maximum leverage of 50% to restrict $w_{i,t}$ to lie between zero and 1.5. Given the optimal weight $w_{i,t}$, the realized portfolio return for country i at time $t+1$ is,

$$R^p_{i,t+1} = w_{i,t} R_{i,t+1} + R^f_{i,t+1}, \quad t = H, ..., T-1, \tag{18}$$

where H is the length of initial estimation period and $R_{i,t+1}$ and $R^f_{i,t+1}$ denote the realized excess stock return and the risk-free return for country i at time $t+1$, respectively.

Over the OOS evaluation period , the CER of the above market timing strategy is

$$\text{CER}_{i,p} = \hat{\mu}_{i,p} - \frac{1}{2}\gamma\hat{\sigma}^2_{i,p}, \tag{19}$$

where $\hat{\mu}_{i,p}$ and $\hat{\sigma}^2_{i,p}$ denote the sample mean and variance of the strategy return realized over the OOS period for country i, respectively. The CER gain of the strategy is then defined as the difference between the strategy's CER and the CER of the benchmark strategy based on the historical average forecast. We report this difference in annualized percentage terms so that it can be interpreted as the annual portfolio management fee that an investor is willing to pay to get access to the forecast generated by a predictive regression instead of using the historical average forecast. We assess the statistical significance of the CER gain using the method described in DeMiguel, Garlappi, and Uppal (2009).

We also report the annualized Sharpe ratio for each portfolio strategy and employ the statistic of Jobson and Korkie (1981) with the correction by Memmel (2003) to test whether the Sharpe ratio of a strategy based on predictive regression forecasts is significantly higher than that of the historical average benchmark strategy. Finally, since the Sharpe ratio could be manipulated (Goetzmann, Ingersoll, Spiegel, and Welch, 2007), we adopt the manipulation-proof performance measure (MPPM, Θ) of Goetzmann et al. (2007) as an alternative measure of the economic value afforded by FVF^{US}. Similarly to CER, we compute the difference between the Θ of a portfolio strategy and the Θ of the historical average benchmark strategy, and we report this difference ($\Delta\Theta$) in annualized percentage terms.

[**Insert Table V here**]

Table V presents the OOS performance of the asset allocation strategy of each country. From the second column, we find that the market timing strategy based on forecasts generated by FVF^{US} produces substantial CER gains relative to the historical average forecasts for all countries except for Japan. For instance, under the risk aversion level of three (Panel A), the positive CER gains range from 2% (Canada) to 5% (France), all significant at the 5% level or better. That is, the investor is willing to pay an annual portfolio management fee up to 5% to switch from the historical average forecast to the forecasts based on FVF^{US}. These values are economically sizable. The third column shows that the CER gains after considering a proportional transaction cost of 50 basis points (bps) remain positive for 10 of the 11 countries, confirming the robustness of the economic value delivered by FVF^{US}.

The fourth through sixth columns of Table V show that in most of the cases, the portfolios based on FVF^{US} achieve remarkably large Sharpe ratios.[17] Under the risk aversion level of five (Panel B), the annualized Sharpe ratios produced by FVF^{US} are significantly higher than those of the historical average strategy for 10 of the 11 countries, and are approximately 1.5 to two times larger than those by the market portfolio (also known as the buy and hold strategy). In addition, the results of MPPM reported in the last two columns reaffirm the robustness of economic gains provided by FVF^{US} relative to the historical average strategy. The positive gains in Θ range from 2.03% (Canada) to 5.35% (the Netherlands) for $\gamma = 3$ and $\rho = 3$, and the results are robust to the consideration of a transaction cost of 50 bps.

Next, we consider an U.S. investor who can invest across the 11 countries and the U.S. risk-free rate. We continue to work with the excess market return in national currency which is a approximate for the currency-hedged equity premium for investors from any country (Solnik, 1993). The portfolio optimization problem faced by the investor becomes,

$$\begin{aligned} &\underset{w_t}{max} \quad w_t'\mu_t - \frac{\gamma}{2} w_t'\Sigma_t w_t \\ &s.t. \quad e'w_t \leq 1.5 \quad 0 \leq w_{i,t} \leq \frac{2}{N}, \quad i = 1, ..., N, \end{aligned} \tag{20}$$

where w_t is the vector of weights on the eleven stock markets, e denotes a vector of one, μ_t is the conditional expected excess stock returns, and Σ_t is the conditional covariance. The investor can either use the OOS excess return forecast produced by the U.S. forward variance factor or the historical average forecast as the estimation for μ_t and estimate Σ_t by the rolling window covariance over the past five years when solving the optimization problem. By doing

[17] Note that a higher CER gain is not necessary to be accompanied by a higher Sharpe ratio. This is because unlike the CER gain, the Sharpe ratio does not penalize for suboptimal leverage (Kan and Zhou, 2007).

so, the difference between two portfolio weights is solely determined by the use of OOS return forecasts. Similarly, we impose a short-sale constraint and a maximum portfolio leverage of 50%. Meanwhile, to produce better-behaved portfolio weights with lower turnover rates, we set an upper bound of $2/N$ on $w_{i,t}$.

According to the last row of Panel A in Table V, the cross-country investment strategy delivers a significantly positive CER gain of 3.28%, a gain in Θ of 3.44%, and a Sharpe ratio of 0.36 that is higher than both the historical average benchmark portfolio and the market portfolio where the investor places an equal weight on each of the eleven markets.[18] The conclusion remains unchanged under $\gamma = 5$ and including a transaction cost of 50 bps.

[**Insert Figure 2 here**]

To shed further light on the behavior of the portfolio based on FVF^{US}, we plot the log cumulative wealth of the portfolios in Figure 2. For the subplots considering a local investment scenario (first 11 subplots), we conclude that the solid line (FVF^{US} portfolio) is predominantly upward sloping for most countries (with the exception of Japan). Though the FVF^{US} portfolio suffers a large loss in wealth during the 2008 Global Financial Crisis, it well catches the market rebound thereafter and grows substantially from the beginning of 2009 to 2019. By contrast, the historical average portfolio takes a more severe drawdown during the crisis and hardly recovers its loss when the market rebounds. The plot for the cross-country investment shows that the historical average portfolio underperforms the naive 1/N portfolio, whereas the FVF^{US} portfolio achieves the best performance among the three. In particular, the FVF^{US} portfolio displays a strong upward trend and consistently outperforms the other two portfolios which ignore the information about U.S. volatility risk over the recent decade, signaling a prominent market timing ability.

In short, our results demonstrate that portfolio strategies based on the U.S. forward variance risk factor FVF^{US} produce hefty economic benefits for investors across countries. Hence, the predictive power of FVF^{US} is significant in both statistical and economic criteria.

[18]DeMiguel et al. (2009) shows that this simple 1/N rule has a superior OOS performance relative to many sophisticated diversification strategies.

5 Sources of Predictability

The previous analysis shows that the U.S. forward variance risk factor FVF^{US} positively predicts equity market returns on the U.S. and the 10 non-US industrialized countries. In this section, we explore the source of the predictive power of FVF^{US}.

5.1 Volatility spillover and global connectedness

Recent literature has documented the central role of the U.S. equity market in the international volatility spillover network (Baele, 2005; Yang and Zhou, 2017). Since foreign market participants require compensations for bearing risks spillover from the U.S. market in terms of expected returns, intuitively, the predictability of FVF^{US} should be correlated with the intensity of volatility spillover from the U.S. to other countries. Furthermore, given the increasing globalization and regional integration, it is of great interest to understand the predictability of FVF^{US} in the context of global connectedness. To substantiate these assertions, we investigate the international volatility spillover network and global connectedness during our sample period following Diebold and Yilmaz (2009, 2014), and then we relate the predictive power of FVF^{US} to the degree of spillover and connectedness.

We collect weekly implied volatility series for the seven countries, including France (V-CAC), Germany (VDAX), Japan (VXJ), the Netherlands (VAEX), Switzerland (V3X), the U.K. (VFTSE), and the U.S. (VIX), that have VIX indices available since 2000, and follow Yang and Zhou (2017) to work with changes in the VIX series to adjust for the high persistence and serial correlation of volatility (Ang et al., 2006). The data are obtained from Datastream. Following Diebold and Yilmaz (2009), we perform the variance decomposition using a structural vector autoregressive (VAR) model of order four with a predictive horizon of four weeks, where the country ordering in the Cholesky-factor identification is guided by the analysis of Yang and Zhou (2017).[19]

[**Insert Figure 3 here**]

[19]Yang and Zhou (2017) employs a network of contemporaneous causal relations to determine the ordering of variables passed to a VAR model. In our case, the order of variables is as follows: VIX, VDAX, VFTSE, V3X, VCAC, VAEX, and Japanese VXJ.

Figure 3 plots net volatility spillovers (contribution to other countries minus contribution received) among the seven countries during the full sample period from January 2000 to June 2019. Node size and edge width are accommodated according to market capitalization and net spillover intensity, respectively. The role of the U.S. clearly stands out. It has the largest market capitalization and amount of volatility spillover to the other six countries, confirming the central role of the U.S. in the global financial market. Due to the spillover effect, the volatility risks in international equity markets rise along with the volatility risk of the U.S. market.[20] Also note that contributions from the U.S. to the variance of the five countries in Europe are in about the same magnitude and markedly larger than the contribution to Japan. This suggests that industrialized countries in Europe are more integrated with the U.S. market than Japan does, providing an intuitive explanation for the more substantial predictability of $\mathrm{FVF}^{\mathrm{US}}$ for countries in Europe than for Japan as indicated by Tables II and IV.

[**Insert Figure 4 here**]

In addition to the previous static analysis, we conduct a dynamic rolling-window analysis of the volatility spillover among the seven countries. Figure 4 plots the total variance decomposition "contributions from others" (dashed line) and "contributions to others" (solid line) estimated using 60-week rolling window for each country over the sample period from March 2001 to June 2019. Since the Y-axes of the first seven subplots are all on the same scale, visually, it is easy to tell that the total volatility spillover from the U.S. to others is predominantly higher than that from any other countries. Particularly, the spillover from the U.S. to other markets reached its maximum level in September 2008 during which Lehman Brothers declared bankruptcy. Besides, we observe spikes in spillovers from the U.K. and from other European countries (Germany and France) when the British government formally announced the withdraw from the European Union. We also present the rolling estimated global connectedness index as calculated in Diebold and Yilmaz (2014) in Figure 4. The degree of connectedness is usually high during market turbulent times, such as the two NBER-dated recessions, and relatively low during tranquil times. Nonetheless, the index is

[20]In untabulated results, we show that U.S. froward variances positively and significantly predict the VIX of the other countries, suggesting that high U.S. forward variances foreshadow high volatility in international markets.

generally higher in the recent decade than before, a sign of increasing global connectedness.

[Insert Table VI here]

Next, we base our understanding of the predictability of FVF^{US} on how it relates to the U.S. spillover intensity and the degree of global connectedness. To this end, we compute R^2_{OS} statistics during periods of high and low U.S. spillover intensity and during high and low global connectedness, that are defined as

$$R^2_{OS,c} = 1 - \frac{\sum_{t=H}^{T-1} I^c_{t+1}(r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{t=H}^{T-1} I^c_{t+1}(r_{i,t+1} - \bar{r}_{i,t+1})^2}, \text{ for c=high, low,} \tag{21}$$

where I^{high}_{t+1} (I^{low}_{t+1}) is set equal to one whenever the total volatility spillover from the U.S. to others or the global connectedness is above (below) its sample mean level in month $t+1$, and zero otherwise. Since the U.S. equity market volatility risk is key to the international equity premium variation, we expect the predictive power of FVF^{US} to be particularly strong during periods with greater volatility spillover from the U.S. and higher connectedness among countries.

Table VI reports the subsample R^2_{OS} statistic calculated based on Eq. (21). Consistent with our expectation, the stronger the spillover effect from the U.S. to other countries, the larger the OOS forecasting gains FVF^{US} generates. In particular, the R^2_{OS} values are uniformly higher and more statistically significant during high-spillover compared to low-spillover periods (except for Japan). This implies that volatility spillovers from the U.S. magnify the local volatility risk and force up the equity premium, giving rise to stronger return predictability. In addition, the fourth and fifth columns show that FVF^{US} produces higher R^2_{OS} statistics for seven of the 10 countries during high-connectedness periods than during low-connectedness periods. This further verifies our assertion that the predictability of FVF^{US} becomes more substantial as connections among countries grow.

To conclude, we illustrate that the U.S. volatility risk has a profound effect on international equity markets in terms of spillovers. Accordingly, FVF^{US} positively predicts future international excess stock returns by predicting a deteriorating investment opportunity set.

5.2 Links to the U.S. economy

Fama and French (1989) and Cochrane (2005) present compelling evidence that the equity premium varies over business cycles: it is relatively high during recessions, peaks at the trough, and drops to normal levels during expansions. They further argue that the stepped-up risk aversion during recessions leads to counter-cyclical risk premia and hence, produces equity premium predictability. Along this line, we conjecture that FVF^{US} predicts U.S. returns through the link between U.S. forward variances and future U.S. economic conditions. Following Rapach et al. (2010) and Chen et al. (2019), we consider several measures proxy for the U.S. economic condition, including the NBER recession indictor (NBER), Chicago Fed National Activity Index (CFNAI), Kansas City Financial Stress Index (KCFSI), Industrial Production Growth (IPG), Nonfarm Payroll rate (Payroll), Smoothed U.S. Recession Probability (SRP), and Aruoba, Diebold, and Scotti (2009) Business Conditions Index (ADS). A detailed description to these variables can be found in the Internet Appendix.

[**Insert Table VII here**]

To very our conjecture formally, we examine the information content of U.S. forward variances about future U.S. economic conditions by running the following predictive regression,

$$y^j_{t+1} = \alpha^j + \beta^j(\text{U.S. FVs})^{\text{PLS}}_t + \varepsilon^j_{t+1}, \tag{22}$$

where y^j is one of the U.S. economic condition measures and (U.S. FVs) is the set of U.S. forward variances (FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m}).[21] We continue to use PLS for dimension reduction and report the estimation results of the above regression in Table VII. We find a significant and inverse relation between U.S. forward variance and future economic conditions. More specifically, the U.S. forward variance positively predicts NBER recessions, financial stress measured by KCFSI, and recession probability, and negatively predicts CFNAI, IPG, and non-farm payroll growth. In particular, high U.S. forward variance predicts future low ADS. Since ADS is a comprehensive indicator of the U.S. business condition summarizing information about the labor market, industrial production, and real

[21] Cochrane (2005) emphasizes that the equity premium forecasts are related to the compensation for business cycle risk if the equity premium predictors are also valid predictors for future economic conditions.

gross domestic product, an increase in the U.S. forward variance implies an increasing probability of economic recession and deteriorating macroeconomic conditions. Therefore, the tight link between the U.S. forward variance and the U.S. economy allows FVF^{US} to capture the equity premium variation induced by changes in economic conditions.

5.3 Links to international economic conditions

Given the key role of the U.S. in the world economy, changes in the U.S. economic condition could have substantial impact on economic conditions in other industrialized countries (Rapach et al., 2013). Since the U.S. forward variance significantly predicts the U.S. economic condition, it presumably predicts the world economy as well. We thus explore how the U.S. forward variances tie to international economic conditions.

Local economic conditions

[**Insert Table VIII here**]

We use IPG as a measure of the local economic condition[22], and run the following predictive regression,

$$\text{IPG}_{i,t+1} = \alpha_i + \beta_i (\text{U.S. FVs})_{i,t}^{\text{PLS}} + \varepsilon_{i,t+1}, \tag{23}$$

where $\text{IPG}_{i,t+1}$ is the IPG (in percent) of country i in month $t+1$, and $(\text{U.S. FVs})_{i,t}^{\text{PLS}}$ is the tth month PLS factor extracted from U.S. forward variances using $\text{IPG}_{i,t+1}$ as the target variable. Intuitively, high U.S. volatility risk makes companies reluctant to expand their productions and thus slows down the world economy, so we expect the U.S. forward variance to negatively predict local economic growth. Panel A of Table VIII reports the estimation results for the above predictive regression. The estimated coefficients of the U.S. forward variance are negative for eight of the nine countries, all of which are significant at the 10% level or better, indicating that high froward variance of the U.S. equity market foreshadows low economic activities in most areas of the world.[23] That is, the U.S. forward variance is

[22]The IPG data for each non-U.S. country is available from Global Financial Data, while we exclude Switzerland since there is a large adjustment to its IPG series in January 2005.

[23]The IPG series of Australia ends in 2016:03. Therefore, in 21 years of monthly data, it may be difficulty to accurately reflect the true relation between the U.S. forward variance and IPG of Australia.

related to future international economic downturns, consistent with the results in Table VII. Besides, we include one-period-lagged growth rate in the regression to control for the mean reverting effect of IPG. The fifth through ninth columns show that IPGs of all countries are highly autocorrelated, while the predictive power of the U.S. forward variance remains significant for most of the countries after controlling for lagged IPG.

Local economic policy uncertainty

In addition, we investigate the relation between the U.S. forward variances and local economic uncertainty. We consider the economic policy uncertainty (EPU) index as proxy for the (policy-related) economic uncertainty of each country and run a predictive regression similar to Eq. (23).[24] Panel B of Table VIII reports the forecasting results for local economic policy uncertainty. We note that the U.S. forward variance positively predicts EPU indices for all countries, with six significant at the 10% level or better. Due to the spike in EPU in 2016 during which the U.K. voted to leave the European Union, the estimated slope coefficient for the U.K. (53.29) is the largest among all estimates. After including for one-period-lagged EPU in the regression, the slope estimates for the U.S. forward variance shrink but remain significant for six countries.

We conclude that future international economic uncertainty is positively related to the present volatility risk in the U.S. equity market. As presented by the model of Pastor and Veronesi (2012), (economic) policy uncertainty is a state variable adversely affecting the investment opportunity set. Consequently, increases in U.S. forward variances imply increasing international economic policy uncertainty that corresponds to adverse shifts in investment opportunities and hence, higher equity premium.

To summarize Table VIII, we show that an increase in the U.S. forward variance signals a decrease in international economic growth and a growing economic uncertainty, that is, a deterioration in international economic conditions. This supports the notion that $\mathrm{FVF}^{\mathrm{US}}$ predicts the international equity premium through its link to the world economy. Moreover, variations in the U.S. forward variance have important implications for the international

[24]The EPU indices for Australia, Canada, France, Germany, Italy, and the U.K. are constructed by Baker et al. (2016). The index for Japan is constructed by Arbatli, Davis, Ito, and Miake (2017), for the Netherlands is by Kroese, Kok, and Parlevliet (2015), and for Sweden is by Armelius, Hull, and Köhler (2017). Switzerland does not have an EPU index.

investment opportunity set. Thus, the predictive power of FVF^{US} is congruous with the international version of ICAPM.

5.4 Investor sentiment

Thus far, we interpret the predictive power of FVF^{US} through the lens of risk-return tradeoff. Nonetheless, recent studies have shown that investor sentiment is of importance in explaining stock return variations (Gao, Ren, and Zhang, 2020; Huang et al., 2015, among others). Intensified U.S. market volatility risk could result in pessimistic sentiments and panic selling among global investors, followed by subsequent price recovery. Thus, the predictability may arise from the link between U.S. forward variances and market sentiment. To disentangle the source of predictive power of FVF^{US}, we examine the relation of U.S. forward variances to the googling investor sentiment indices of Gao et al. (2020) for the U.S. and the 10 non-U.S. industrialized countries by running the following predictive regression,

$$\text{SENTI}_{i,t+1} = \alpha_i + \beta_i(\text{U.S. FVs})^{\text{PLS}}_{i,t} + \gamma_i \text{SENTI}_{i,t} + \varepsilon_{i,t+1}, \tag{24}$$

where $\text{SENTI}_{i,t+1}$ is the googling sentiment index of country i in month $t+1$, and $(\text{U.S. FVs})^{\text{PLS}}_{i,t}$ is the tth month PLS factor extracted from U.S. forward variances using $\text{SENTI}_{i,t+1}$ as the target variable.[25]

[**Insert Table IX here**]

Table IX presents the results of forecasting investor sentiment. We observe a positive relation prevailing between the U.S. forward variance and country-specific sentiment indices (except for Italy and the U.K.). This finding is consistent with the positive intertemporal relation between FVF^{US} and the expected excess stock return since investor sentiment is positively correlated with stock returns contemporaneously in the data. That is, high U.S. volatility risk predicts high sentiment associated with high excess stock returns. The estimated regression coefficients for U.S. forward variances, however, are generally insignificant at the conventional significant level. Therefore, it is implausible that the predictability of FVF^{US} derives from a sentiment channel.

[25]Since the Googling sentiment index of Gao et al. (2020) measures the change in investor sentiment at a weekly frequency, we approximate the monthly index by adding sentiment indices within the month.

6 Robustness analysis

6.1 U.S. dollar-denominated stock returns

Our baseline analysis focuses on the predictability of stock returns in national currency. Nevertheless, it is also of significance to study the predictive power of U.S. forward variances for international stock returns in the presence of exchange rate risks. We thus repeat the forecasting analysis performed in sections 4.1 and 4.2 while replacing the excess log stock market return denominated in local currency by the U.S. dollar-denominated return.

[**Insert Table X here**]

Table X reports the forecasting results for U.S. dollar-denominated returns. Working with the U.S. dollar-denominated return barely changes our main conclusion. The relation between FVF^{US} and future excess log market returns remains positive and is significant for all countries except for Japan. However, compared to results in Table II, the values of R^2 slightly drop, ranging from a low of 0.52% for Japan to a high of 3.82% for Switzerland. Perhaps the time variations of exchange rate risk premium are not well captured by the U.S. forward variance derived form the equity option market. The fifth and sixth columns show that the forecasting gain of FVF^{US} relative to the historical average benchmark exists in both recession and expansion periods, while R^2_{Rec} values are uniformly greater than the corresponding R^2_{Exp} values, reaffirming the counter-cyclical forecasting performance of FVF^{US}. In addition, the pooled OLS regression reported in the last row implies that on average, a one-standard-deviation increase in FVF^{US} leads to a rise in the monthly international equity premium of 0.71%, which is lower than the 0.78% when returns are denominated in local currency (Table II). This could be potentially due to the opposite direction in the movements of equity and exchange rate returns (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012). Finally, as shown in the Internet Appendix, the predictive power of FVF^{US} remains significant after controlling for local economic variables, local volatility risk, and alternative U.S. predictors.

6.2 Country-specific forward variance risk factor

[**Insert Table XI here**]

In our baseline analyses, we construct the U.S. forward variance risk factor $\mathrm{FVF}^{\mathrm{US}}$ using the U.S. return as the target proxy in PLS. In this subsection, we consider individual stock market returns as the target proxies in PLS to obtain country-specific forward variance risk factors for each country i, denoted as $\mathrm{FVF}_i^{\mathrm{US}}$. We then test their predictive ability by running the following predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_{i,t}^{\mathrm{US}} + \varepsilon_{i,t+1},$$

where r_i is the the logarithm market return of country i and $\mathrm{FVF}_i^{\mathrm{US}}$ is the forward variance risk factor for country i. As presented in Table XI, country-specific forward variance risk factors significantly predict eight of the 10 non-U.S. counties, and produce higher R^2_{OS} values for eight counties than $\mathrm{FVF}^{\mathrm{US}}$ does. Perhaps not surprisingly, $\mathrm{FVF}_i^{\mathrm{US}}$ captures country-specific risks and thus evinces stronger predictive power. However, we note that $\mathrm{FVF}^{\mathrm{US}}$ alone achieves comparably well forecasting performance for the 10 non-U.S. counties, implying that these countries are well integrated with the U.S. equity market and more importantly, reaffirming that U.S. volatility is a global risk that has been priced into international equity premia.

6.3 Subsample analysis

[**Insert Table XII here**]

To ensure that the predictive ability of $\mathrm{FVF}^{\mathrm{US}}$ is not sensitive to the choice of sample period, we consider three different subsamples, from February 1996 to October 2007 (the first-half sample), from November 2007 to June 2019 (the second-half sample), and the sample excluding for observations during 2008 recession (from January 2008 to June 2009). According to Table XII, we find good temporal stability in the β estimates for $\mathrm{FVF}^{\mathrm{US}}$ for all the subsamples. That is, the β estimates are mostly positive and significant. All the same, the magnitude and t-statistics of slope estimates and R^2 values in the second-half sample rise considerably. The stronger predictability uncovered for the second-half sample relative to the first-half is congruous with our finding in section 5.1 that the global connectedness has increased since 2008 Global Financial Crisis. Besides, the eighth through tenth columns show that excluding the period of 2008 recession weakens the predictive power of FVF^{US}. This is not surprising since return predictability is found to be concentrated in subsamples with deep recessions (Henkel et al., 2011; Rapach et al., 2010). Nevertheless, FVF^{US} continues to significantly predict market returns of eight countries including the U.S., revealing that the strong forecasting performance of FVF^{US} steps from the whole sample period rather than some particular subsamples.

6.4 Emerging markets

[**Insert Table XIII here**]

In addition to the 10 developed markets, we further consider 14 emerging markets: Greece, Hungary, Poland, South Africa, Brazil, Colombia, Mexico, China (Mainland), India, Malaysia, Pakistan, Philippines, Taiwan, and Thailand. The selection of the markets is dictated by data availability. We obtain the stock market returns and local risk-free rates for emerging markets from GFD. Table XIII reports the forecasting results for these emerging markets. In general, we find positive relations between FVF^{US} and future excess returns of the emerging markets. For instance, FVF^{US} positively forecasts returns of China (Mainland) , consistent with the finding of Chen et al. (2017) that the U.S. volatility risk positively predicts Chinese daytime stock returns. However, in comparison with the results of developed markets, the predictive power of FVF^{US} for emerging markets is insignificant. Bekaert and Harvey (1995) show that risk premia of countries that are segmented from world capital markets mainly come from rewards to local risks rather than global risks. Since emerging markets are less integrated with world capital markets, the U.S. in particular, due to capital controls or/and poorly developed financial market (Bekaert et al., 2011), the U.S. volatility risk has limited impact on their equity premia. This in turn results in weak ability of FVF^{US} to explain emerging markets' expected returns.

7 Conclusion

In this paper, we investigate the cross-country role of the U.S. stock market volatility in international equity markets. Using the PLS method, we construct a U.S. forward variance risk factor based on the term structure of forward variances implied from the S&P 500 option data. The factor significantly predicts U.S. returns and 10 non-U.S. industrialized countries' returns from January 1996 to June 2019 both in- and out-of-sample. The results are robust to different measurements of returns (in national currencies or U.S. dollar) and the inclusion of domestic predictors and U.S. predictive variables in the extant literature. In addition, the asset allocation analysis reveals that the predictive ability afforded by the U.S. forward variance risk factor can produce considerable economic gains to a mean-variance investor.

In the Merton's ICAPM, the equity premium contains compensations for market volatility risk as well as state variable risks related to shifts in the investment opportunity set. In particular, there is a conditional positive relation between the market variance and expected market returns. Our finding is consistent with this positive risk-return relation implied by the ICAPM. We provide rich evidence showing that the U.S. forward variance is closely related to the future U.S. and international economic and financial conditions. Therefore, the U.S. forward variance risk factor predicts market returns through its link to the future economic fluctuations and its ability to characterize the time-varying global investment opportunities. In addition, we find more substantial predictability of the factor during periods with stronger U.S. volatility spillover effect and higher global connectedness. Overall, our findings are in line with the implication of an international version of the ICAPM, and highlight the leading role of U.S. volatility in the international risk-return tradeoff relation.

References

Andreou, P. C., Kagkadis, A., Philip, D., Taamouti, A., 2019. The information content of forward moments. Journal of Banking & Finance 106, 527–541.

Ang, A., Bekaert, G., 2007. Stock return predictability: Is it there? Review of Financial Studies 20, 651–707.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Aono, K., Iwaisako, T., 2011. Forecasting Japanese stock returns with financial ratios and other variables. Asia-Pacific Financial Markets 18, 373–384.

Arbatli, E. C., Davis, S. J., Ito, A., Miake, N., 2017. Policy uncertainty in Japan. Tech. rep., National Bureau of Economic Research.

Armelius, H., Hull, I., Köhler, H. S., 2017. The timing of uncertainty shocks in a small open economy. Economics Letters 155, 31–34.

Aruoba, S. B., Diebold, F. X., Scotti, C., 2009. Real-time measurement of business conditions. Journal of Business & Economic Statistics 27, 417–427.

Baele, L., 2005. Volatility spillover effects in European equity markets. Journal of Financial and Quantitative Analysis 40, 373–401.

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131, 1593–1636.

Bakshi, G., Kapadia, N., 2003. Delta-hedged gains and the negative market volatility risk premium. Review of Financial Studies 16, 527–566.

Bakshi, G., Panayotov, G., Skoulakis, G., 2011. Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios. Journal of Financial Economics 100, 475–495.

Bali, T. G., 2008. The intertemporal relation between expected returns and risk. Journal of Financial Economics 87, 101–131.

Bali, T. G., Engle, R. F., 2010. The intertemporal capital asset pricing model with dynamic conditional correlations. Journal of Monetary Economics 57, 377–390.

Bali, T. G., Peng, L., 2006. Is there a risk–return trade-off? evidence from high-frequency data. Journal of Applied Econometrics 21, 1169–1198.

Bansal, R., Kiku, D., Shaliastovich, I., Yaron, A., 2014. Volatility, the macroeconomy, and asset prices. Journal of Finance 69, 2471–2511.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.

Bekaert, G., Harvey, C., Ng, A., 2005. Market integration and contagion. Journal of Business 78, 39–70.

Bekaert, G., Harvey, C. R., 1995. Time-varying world market integration. Journal of Finance 50, 403–444.

Bekaert, G., Harvey, C. R., Lundblad, C. T., Siegel, S., 2011. What segments equity markets? Review of Financial Studies 24, 3841–3890.

Bekaert, G., Hodrick, R. J., Zhang, X., 2009. International stock return comovements. Journal of Finance 64, 2591–2626.

Bekaert, G., Hoerova, M., 2014. The VIX, the variance premium and stock market volatility. Journal of Econometrics 183, 181–192.

Black, F., 1976. Studies of stock market volatility changes. In: *Proceedings of the American Statistical Association Business and Economic Statistics Section*, American Statistical Association.

Bollerslev, T., Marrone, J., Xu, L., Zhou, H., 2014. Stock return predictability and variance risk premia: statistical inference and international evidence. Journal of Financial and Quantitative Analysis 49, 633–661.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. Review of Financial Studies 22, 4463–4492.

Britten-Jones, M., Neuberger, A., 2000. Option prices, implied price processes, and stochastic volatility. Journal of Finance 55, 839–866.

Buncic, D., Gisler, K. I., 2016. Global equity market volatility spillovers: A broader role for the united states. International Journal of Forecasting 32, 1317–1339.

Busch, T., Christensen, B. J., Nielsen, M. Ø., 2011. The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. Journal of Econometrics 160, 48–57.

Campbell, J., 1993. Intertemporal asset pricing without consumption data. American Economic Review 83, 487–512.

Campbell, J. Y., Giglio, S., Polk, C., Turley, R., 2018. An intertemporal CAPM with stochastic volatility. Journal of Financial Economics 128, 207–233.

Campbell, J. Y., Thompson, S. B., 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Carr, P., Madan, D., 2001. Towards a theory of volatility trading. In: *Option Pricing, Interest Rates and Risk Management, Handbooks in Mathematical Finance*, Cambridge University Press, pp. 458–476.

Carr, P., Wu, L., 2009. Variance risk premiums. Review of Financial Studies 22, 1311–1341.

CBOE, 2009. White Paper Cboe Volatility Index.

Chauvet, M., 1998. An econometric characterization of business cycle dynamics with factor structure and regime switching. International Economic Review 39, 969–96.

Chen, J., 2002. Intertemporal CAPM and the cross-section of stock returns. In: *EFA 2002 Berlin Meetings Discussion Paper*.

Chen, J., Jiang, F., Liu, Y., Tu, J., 2017. International volatility risk and Chinese stock return predictability. Journal of International Money and Finance 70, 183–203.

Chen, J., Jiang, F., Xue, S., Yao, J., 2019. The world predictive power of US equity market skewness risk. Journal of International Money and Finance 96, 210–227.

Chen, N.-f., Zhang, F., 1997. Correlations, trades and stock returns of the Pacific-Basin markets. Pacific-Basin Finance Journal 5, 559–577.

Clark, T. E., West, K. D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291–311.

Cochrane, J. H., 2005. Financial markets and the real economy. Foundations and Trends® in Finance 1, 1–101.

Cremers, M., Halling, M., Weinbaum, D., 2015. Aggregate jump and volatility risk in the cross-section of stock returns. Journal of Finance 70, 577–614.

Darolles, S., Gourieroux, C., Jasiak, J., 2006. Structural Laplace transform and compound autoregressive models. Journal of Time Series Analysis 27, 477–503.

DeMiguel, V., Garlappi, L., Uppal, R., 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? Review of Financial Studies 22, 1915–1953.

Diebold, F. X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal 119, 158–171.

Diebold, F. X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.

Duffie, D., Pan, J., Singleton, K., 2000. Transform analysis and asset pricing for affine jump-diffusions. Econometrica 68, 1343–1376.

Eraker, B., 2008. Affine general equilibrium models. Management Science 54, 2068–2080.

Fama, E. F., French, K. R., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23–49.

Feunou, B., Fontaine, J.-S., Taamouti, A., Tédongap, R., 2014. Risk premium, variance premium, and the maturity structure of uncertainty. Review of Finance 18, 219–269.

Gao, Z., Ren, H., Zhang, B., 2020. Googling investor sentiment around the world. Journal of Financial and Quantitative Analysis 55, 549–580.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-off after all. Journal of Financial Economics 76, 509–548.

Goetzmann, W., Ingersoll, J., Spiegel, M., Welch, I., 2007. Portfolio performance manipulation and manipulation-proof performance measures. Review of Financial Studies 20, 1503–1546.

Guo, H., Whitelaw, R. F., 2006. Uncovering the risk–return relation in the stock market. Journal of Finance 61, 1433–1463.

Hamao, Y., Masulis, R. W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. Review of Financial Studies 3, 281–307.

Harvey, D. I., Leybourne, S. J., Newbold, P., 1998. Tests for forecast encompassing. Journal of Business & Economic Statistics 16, 254–259.

Henkel, S. J., Martin, J. S., Nardari, F., 2011. Time-varying short-horizon predictability. Journal of Financial Economics 99, 560–580.

Hjalmarsson, E., 2010. Predicting global stock returns. Journal of Financial and Quantitative Analysis pp. 49–80.

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28, 791–837.

Jiang, G. J., Tian, Y. S., 2005. The model-free implied volatility and its information content. Review of Financial Studies 18, 1305–1342.

Jobson, J. D., Korkie, B. M., 1981. Performance hypothesis testing with the sharpe and treynor measures. Journal of Finance 36, 889–908.

Kacperczyk, M., Van Nieuwerburgh, S., Veldkamp, L., 2016. A rational theory of mutual funds' attention allocation. Econometrica 84, 571–626.

Kan, R., Zhou, G., 2007. Optimal portfolio choice with parameter uncertainty. Journal of Financial and Quantitative Analysis 42, 621–656.

Kelly, B., Pruitt, S., 2013. Market expectations in the cross-section of present values. Journal of Finance 68, 1721–1756.

Kelly, B., Pruitt, S., 2015. The three-pass regression filter: A new approach to forecasting using many predictors. Journal of Econometrics 186, 294–316.

Kozhan, R., Neuberger, A., Schneider, P., 2013. The skew risk premium in the equity index market. Review of Financial Studies 26, 2174–2203.

Kroese, L., Kok, S., Parlevliet, J., 2015. Beleidsonzekerheid in nederland. Economisch Statistiche Berichten 4715, 464–467.

Lettau, M., Ludvigson, S. C., 2010. Chapter 11 - measuring and modeling variation in the risk-return trade-off. In: At-Sahalia, Y., Hansen, L. P. (eds.), *Handbook of Financial Econometrics: Tools and Techniques*, North-Holland, San Diego, vol. 1 of *Handbooks in Finance*, pp. 617–690.

Londono, J. M., 2015. The variance risk premium around the world.

Ludvigson, S. C., Ng, S., 2007. The empirical risk–return relation: A factor analysis approach. Journal of Financial Economics 83, 171–222.

Luo, X., Zhang, J. E., 2017. Expected stock returns and forward variance. Journal of Financial Markets 34, 95–117.

Maio, P., Santa-Clara, P., 2012. Multifactor models and their consistency with the ICAPM. Journal of Financial Economics 106, 586–613.

Memmel, C., 2003. Performance hypothesis testing with the sharpe ratio. Finance Letters 1, 21–23.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Carry trades and global foreign exchange volatility. Journal of Finance 67, 681–718.

Merton, R. C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867–887.

Merton, R. C., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323–361.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. Journal of Finance 67, 1219–1264.

Rapach, D. E., Strauss, J. K., Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. Review of Financial Studies 23, 821–862.

Rapach, D. E., Strauss, J. K., Zhou, G., 2013. International stock return predictability: What is the role of the united states? Journal of Finance 68, 1633–1662.

Rossi, A. G., Timmermann, A., 2015. Modeling covariance risk in Merton's ICAPM. Review of Financial Studies 28, 1428–1461.

Sarno, L., Schneider, P., Wagner, C., 2012. Properties of foreign exchange risk premiums. Journal of Financial Economics 105, 279–310.

Solnik, B., 1993. The performance of international asset allocation strategies using conditioning information. Journal of Empirical Finance 1, 33–55.

Welch, I., Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

Wold, H., 1966. Estimation of principal components and related models by iterative least squares. In: Krishnaiaah, P. (ed.), *Multivariate Analysis*, New York: Academic Press, pp. 391–420.

Yang, Z., Zhou, Y., 2017. Quantitative easing and volatility spillovers across countries and asset classes. Management Science 63, 333–354.

Table I: **Summary statistics**

The table shows the summary statistics for the monthly log stock market returns of eleven developed countries and for the term structure of U.S. risk-neutral forward variances. The eleven countries include Australia (AUS), Canada (CAN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the Netherlands (NLD), Sweden (SWE), Switzerland (CHE), the United Kingdom (GBR), and the United States (USA). The market returns are denominated in domestic currencies. The U.S. forward variances are the risk-neutral variances of the S& 500 index return over certain future time horizons, and are calculated as the differences between pairs of the risk-neutral variances with different maturity days. FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m} are the U.S. forward variances over three to six, six to nine, nine to twelve, and twelve to eighteen months ahead. Panel A reports mean, standard deviation, skewness, kurtosis, median, minimum, maximum, and the first-order autocorrelation coefficient (AR(1)). Panel B reports the correlation matrices. The sample period ranges from January 1996 to June 2019.

(1)	(2) **Mean**	(3) **Std**	(4) **Skew**	(5) **Kurt**	(6) **Median**	(7) **Min**	(8) **Max**	(9) **AR(1)**
Panel A. Descriptive statistics								
Excess stock market returns (%)								
Australia	0.38	3.66	−0.98	4.57	0.93	−15.52	7.53	0.07
Canada	0.44	4.23	−1.31	7.74	0.98	−22.86	10.98	0.19
France	0.54	5.16	−0.73	4.00	1.13	−18.88	12.90	0.11
Germany	0.45	5.83	−0.91	5.72	1.09	−27.48	18.07	0.09
Italy	0.34	5.96	−0.10	3.79	0.78	−17.50	20.31	0.00
Japan	0.11	5.09	−0.48	3.91	0.44	−22.68	12.80	0.15
Netherlands	0.45	5.36	−1.16	5.75	1.30	−21.61	12.47	0.11
Sweden	0.68	5.65	−0.62	4.54	1.25	−20.07	18.70	0.12
Switzerland	0.55	4.32	−0.95	5.19	1.29	−20.08	11.53	0.17
United Kingdom	0.31	3.90	−0.84	4.33	0.93	−14.62	9.43	0.04
United States	0.53	4.34	−0.84	4.54	1.01	−18.46	10.37	0.05
U.S. forward variances (%)								
FV_{3m6m}	1.31	0.76	2.02	8.22	1.11	0.39	4.90	0.91
FV_{6m9m}	1.32	0.70	1.93	7.79	1.16	0.46	4.45	0.91
FV_{9m12m}	1.46	0.73	1.49	5.29	1.25	0.53	4.24	0.90
FV_{12m18m}	2.80	1.32	1.32	4.77	2.54	1.03	7.23	0.90

Panel B. Correlation matrix

Excess stock market returns

	AUS	CAN	FRA	DEU	ITA	JPN	NLD	SWE	CHE	GBR
AUS		0.68	0.69	0.67	0.62	0.58	0.69	0.65	0.63	0.74
CAN	0.68		0.70	0.68	0.61	0.50	0.71	0.66	0.61	0.72
FRA	0.69	0.70		0.92	0.86	0.58	0.91	0.86	0.82	0.84
DEU	0.67	0.68	0.92		0.80	0.56	0.88	0.86	0.77	0.81
ITA	0.62	0.61	0.86	0.80		0.53	0.81	0.73	0.72	0.75
JPN	0.58	0.50	0.58	0.56	0.53		0.56	0.56	0.55	0.54
NLD	0.69	0.71	0.91	0.88	0.81	0.56		0.83	0.82	0.85
SWE	0.65	0.66	0.86	0.86	0.73	0.56	0.83		0.73	0.77
CHE	0.63	0.61	0.82	0.77	0.72	0.55	0.82	0.73		0.76
GBR	0.74	0.72	0.84	0.81	0.75	0.54	0.85	0.77	0.76	
USA	0.71	0.78	0.79	0.79	0.66	0.57	0.78	0.73	0.74	0.81

U.S. forward variances

	FV_{3m6m}	FV_{6m9m}	FV_{9m12m}	FV_{12m18m}
FV_{3m6m}		0.97	0.92	0.91
FV_{6m9m}	0.97		0.93	0.94
FV_{9m12m}	0.92	0.93		0.91
FV_{12m18m}	0.91	0.94	0.91	

Table II: **In-sample estimation results: Univariate analysis**

This table shows the in-sample estimation results of the univariate predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_t^{\mathrm{US}} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the excess log market return of country i at month $t+1$, and $\mathrm{FVF}_t^{\mathrm{US}}$ is the month-t PLS forward variance factor extracted from the term structure of U.S. forward variances. $\mathrm{FVF}_t^{\mathrm{US}}$ is standardized to have zero mean and unit variance. Stock returns are denominated in domestic currencies. We follow Kelly and Pruitt (2015) to compute the t-statistic of the β estimate. The fifth and sixth columns report the subsample R^2 statistics over NBER-dated business cycle recessions (R^2_{Rec}) and expansions (R^2_{Exp}). The last row presents the pooled OLS regression estimates where the restriction that β_is are the same for all countries is imposed. The t-statistics of pooled estimates are based on the GMM, following Ang and Bekaert (2007). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from February 1996 to June 2019.

(1)	(2) $\beta(\%)$	(3) t-stat	(4) $R^2(\%)$	(5) $R^2_{Rec}(\%)$	(6) $R^2_{Exp}(\%)$
Australia	0.48	1.68*	1.71	7.03	−0.53
Canada	0.49	1.88*	1.32	2.99	0.77
France	1.02	2.82***	3.90	10.88	1.78
Germany	1.04	2.52**	3.22	10.24	1.22
Italy	0.93	2.97***	2.43	8.25	1.00
Japan	0.34	0.88	0.45	2.71	−0.17
Netherlands	0.95	2.76***	3.14	7.84	1.34
Sweden	0.89	2.38**	2.50	6.52	1.23
Switzerland	1.06	3.86***	6.00	14.46	4.08
United Kingdom	0.68	2.96***	3.06	6.92	1.80
United States	0.68	2.53**	2.44	4.98	1.58
Pooled	0.78	2.78***	2.58		

Table III: **In-sample estimation results: Multivariate analysis**

The table shows the results controlling for local economic conditions, local volatility risk, and alternative U.S. predictive variables. Panel A reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{TBL}_{i,t} + \beta_{i,3}\mathrm{DY}_{i,t} + \beta_{i,4}\mathrm{TMS}_{i,t} + \beta_{i,5}\mathrm{Jan}_{t+1} + \varepsilon_{i,t+1}$$

where $\mathrm{FVF}^{\mathrm{US}}$ is the U.S. forward variance risk factor, TBL_i is the three-month treasury bill rate of country i, DY_i is the dividend yield of country i, TMS_i is the term spread, and Jan is the January dummy. Panel B reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{SVAR}_{i,t} + \varepsilon_{i,t+1}$$

where $\mathrm{SVAR}_{i,t}$ is the stock variance of country i. Panel C reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{SKEW}_t^{\mathrm{US}} + \beta_{i,3}\mathrm{VRP}_t^{\mathrm{US}} + \beta_{i,4} r_{\mathrm{US},t} + \varepsilon_{i,t+1}$$

where $\mathrm{SKEW}^{\mathrm{US}}$ is the monthly innovation in the U.S. stock market skewness, $\mathrm{VRP}^{\mathrm{US}}$ is the U.S. variance risk premium of Bollerslev et al. (2009), and r_{US} is the lagged U.S. return. The coefficient estimates (in percentage), the associated Newey-West t-statistics, and the R^2 statistic of each regression are reported. The last row of each Panel reports the pooled OLS estimates where the restriction that β^is are the same for all countries is imposed. The t-statistics of pooled estimates are based on the GMM, following Ang and Bekaert (2007). Stock returns are denominated in domestic currencies. All predictive variables are standardized to have zero mean and unit variance. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from February 1996 to June 2019.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: controlling for local financial and economic variables											
	$\mathrm{FVF}^{\mathrm{US}}$		**TBL**		**DY**		**TMS**		**Jan**		
	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	R^2(%)
Australia	0.45	1.72*	−0.18	−0.55	0.14	0.36	0.33	1.20	−0.78	−0.97	3.84
Canada	0.50	1.68*	−0.02	−0.05	0.11	0.18	0.32	0.97	0.66	0.93	2.17
France	1.02	2.75***	−0.59	−1.65*	−0.48	−1.08	0.77	2.53**	0.25	0.24	7.27
Germany	1.06	2.74***	−0.91	−2.03**	−0.47	−0.85	0.80	2.61***	0.24	0.20	6.89
Italy	0.95	3.31***	−0.19	−0.39	−0.67	−1.14	0.33	0.68	1.53	1.21	3.76
Japan	0.34	0.89	−1.01	−2.30**	0.25	0.44	0.39	0.70	−0.55	−0.53	3.80
Netherlands	0.93	2.98***	−0.56	−1.91*	−0.26	−0.62	0.96	2.54**	−0.37	−0.38	8.64
Sweden	0.97	2.36**	−0.31	−0.88	0.66	1.39	1.59	4.22***	0.26	0.23	10.06
Switzerland	1.06	3.87***	−1.00	−2.27**	−0.64	−1.07	0.29	0.76	−0.41	−0.45	10.42
United Kingdom	0.62	2.47**	−0.09	−0.36	0.41	1.12	0.08	0.26	−1.27	−1.50	5.60
United States	0.62	2.16**	−0.07	−0.17	0.62	1.35	−0.37	−0.99	−0.31	−0.34	4.50
Pooled	0.78	2.89***	−0.43	−1.57	−0.11	−0.34	0.38	2.29**	−0.06	−0.08	4.15

Panel B: controlling for local volatility risk					
	$\mathrm{FVF}^{\mathrm{US}}$		**SVAR**		
	β(%)	t-stat	β(%)	t-stat	R^2(%)
Australia	0.48	1.70*	−0.47	−1.81*	3.38
Canada	0.48	1.69*	−0.65	−2.31**	3.70
France	1.04	2.58***	−0.35	−1.03	4.35
Germany	1.06	2.54**	−0.21	−0.49	3.35
Italy	0.92	3.12***	0.04	0.10	2.43
Japan	0.34	0.82	−0.17	−0.94	0.56
Netherlands	0.98	2.71***	−0.47	−1.22	3.89
Sweden	0.90	2.23**	−0.08	−0.20	2.52
Switzerland	1.09	3.30***	−0.31	−1.25	6.50
United Kingdom	0.68	2.80***	−0.07	−0.27	3.10
United States	0.68	2.54**	−0.64	−1.79*	4.58
Pooled	0.79	2.86***	−0.30	−1.13	2.94

Panel C: controlling for alternative U.S. predictors	**FVF^{US}**		**SKEW^{US}**		**VRP^{US}**		**lagged US Return**		
	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	R^2(%)
Australia	0.36	1.22	0.01	0.04	0.55	3.29***	0.35	1.31	5.18
Canada	0.33	1.31	0.17	0.89	0.45	1.95*	0.66	2.18**	5.18
France	0.89	2.24**	0.48	1.83*	0.24	0.66	0.60	1.60	6.08
Germany	0.90	2.11**	0.37	1.34	0.34	0.99	0.66	1.69*	5.15
Italy	0.81	2.68***	0.31	1.02	0.12	0.32	0.68	1.57	3.81
Japan	0.27	0.62	0.25	0.95	−0.18	−0.69	0.57	1.46	1.69
Netherlands	0.82	2.13**	0.44	1.72*	−0.06	−0.17	0.86	1.98**	5.70
Sweden	0.81	1.95*	0.22	0.82	0.20	0.51	0.41	0.98	3.25
Switzerland	0.97	3.04***	0.21	1.01	−0.11	−0.33	0.62	2.01**	7.90
United Kingdom	0.63	2.56**	0.25	1.23	0.20	0.84	0.21	0.78	4.01
United States	0.54	2.25**	0.21	1.05	0.87	3.50***	0.23	0.74	7.28
Pooled	0.67	2.27**	0.27	1.34	0.24	0.96	0.53	1.56	4.17

Table IV: **Out-of-sample forecasting results**

The table reports the OOS forecasting results of the U.S. forward variance risk factor. The second, third, and fourth columns in Panel A show the OOS R^2 values over the whole period (R^2_{OS}), NBER-dated business cycle recessions ($R^2_{OS,Rec}$), and business cycle expansions ($R^2_{OS,Exp}$), respectively. We use the Clark and West (2007) MSFE-adjusted statistic that tests the null hypothesis $R^2_{OS} \leq 0$ against the alternative one $R^2_{OS} > 0$ to assess the significance of R^2_{OS} values. Panel B reports the results of encompassing tests. The test is conducted by constructing the following optimal composite forecast,

$$\hat{r}^{*}_{i,t+1} = (1-\lambda)\hat{r}^{\text{Comp}}_{i,t+1} + \lambda \hat{r}^{\text{FVF}^{\text{US}}}_{i,t+1}, \quad 0 \leq \lambda \leq 1$$

where $\hat{r}_i^{\text{FVF}^{\text{US}}}$ ($\hat{r}_i^{\text{Comp}}$) is the forecast for country i's market return generated by the U.S. forward variance risk factor (the competing models based on the control variables described in Table III). We use the Harvey et al. (1998) statistic to test the null hypothesis that $\lambda = 0$, indicating that the competing model encompasses FVF^{US}, against the alternative hypothesis $\lambda > 0$ that the competing model does not encompass FVF^{US}. We present p-values for the Harvey et al. (1998) statistic in the fifth through seventh columns. Stock returns are denominated in domestic currencies. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The OOS period ranges from February 2001 to June 2019.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Out-of-sample R^2(%)			**Panel B: *HLN* statistic *p*-value**		
	R^2_{OS}	$R^2_{OS,Rec}$	$R^2_{OS,Exp}$	local Econ	local SVAR	US predictors
Australia	1.18*	2.59**	0.36	0.00	0.05	0.26
Canada	1.50**	3.56**	0.20	0.00	0.13	0.08
France	3.59**	7.90**	1.69*	0.00	0.00	0.00
Germany	2.91**	7.32**	1.22*	0.00	0.00	0.01
Italy	2.88**	7.03**	1.11*	0.01	0.02	0.01
Japan	−0.09	−3.03	0.98***	0.00	0.13	0.05
Netherlands	2.53**	4.61**	1.38*	0.00	0.00	0.01
Sweden	3.11**	7.51**	1.11*	0.00	0.00	0.00
Switzerland	4.37***	10.23**	2.10**	0.00	0.00	0.00
United Kingdom	1.91*	7.82**	−0.62	0.00	0.01	0.01
United States	2.17**	6.01**	0.31	0.00	0.01	0.07

Table V: **Asset allocation performance**

The table reports the asset allocation performance for a mean–variance investor who allocates monthly between the stocks and risk-free bills using the OOS market excess return forecast based on the U.S. forward variance risk factor (FVF^{US}). Panel A (B) assumes a risk aversion coefficient of three (five) of the investor. The local investment strategy considers an investor who invests in local market only, and the cross-country strategy considers an U.S. investor who invests across countries with risk-free bills from the U.S. market. The portfolio performance measures include the gains in certainty equivalent return (CER gain, in annualized percentage terms) relative to the benchmark, the Sharpe ratio (annualized), and the gains in the manipulation-proof performance measure relative to the benchmark ($\triangle\boldsymbol{\Theta}$, in annualized percentage term). We also report the CER gain and $\triangle\boldsymbol{\Theta}$ after considering 50 basis points transaction cost. The benchmark portfolio strategy is formed based on the historical average forecast (HAV). The significance of the CER gain is determined by the method outlined by DeMiguel et al. (2009). The significance of the difference between the Sharpe ratio of portfolio based on FVF^{US} from that of HAV is assessed by the Jobson and Korkie (1981)'s statistic corrected by Memmel (2003). The sixth column reports the annualized market (equal-weighted portfolio) Sharpe ratio for each country (cross-country). Stock returns are denominated in domestic currencies. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The OOS period ranges from February 2001 to June 2019.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CER Gain(%)		**Sharpe Ratio**			**$\triangle\Theta$(%)**	
	No cost	50 bps	HAV	FVF^{US}	Market	No cost	50 bps
Panel A: $\gamma = 3$							
Local Investment							
Australia	2.19**	0.99	0.30	0.46**	0.39	2.27	1.08
Canada	2.00**	0.72	0.27	0.41*	0.36	2.03	0.75
France	5.00***	3.45**	0.01	0.29**	0.23	5.26	3.69
Germany	4.92**	3.59*	−0.06	0.34***	0.25	5.17	3.82
Italy	4.50**	3.16*	−0.19	0.16***	0.07	4.75	3.39
Japan	−0.26	−0.56	−0.02	−0.04	0.24	−0.29	−0.59
Netherlands	5.00***	3.84**	−0.05	0.24**	0.18	5.35	4.19
Sweden	4.45**	3.06*	0.15	0.39**	0.35	4.81	3.41
Switzerland	2.95**	1.26	0.26	0.43*	0.34	3.04	1.36
United Kingdom	4.06***	2.50*	0.03	0.45***	0.28	4.13	2.58
United States	3.48**	1.77	0.18	0.42**	0.40	3.51	1.78
Cross-country Investment							
Cross-country	3.28**	1.80	0.15	0.36**	0.31	3.44	1.95
Panel B: $\gamma = 5$							
Local Investment							
Australia	2.45**	1.55*	0.27	0.52**	0.39	2.68	1.78
Canada	2.55**	1.50*	0.25	0.46**	0.36	2.75	1.71
France	4.61***	3.39**	−0.07	0.35***	0.23	5.16	3.92
Germany	2.98**	2.03	−0.06	0.37***	0.25	3.29	2.31
Italy	3.76**	2.85*	−0.26	0.18***	0.07	4.41	3.46
Japan	−0.59	−0.82	−0.02	−0.11	0.24	−0.67	−0.91
Netherlands	4.19***	3.26***	−0.07	0.34***	0.18	4.48	3.54
Sweden	3.68**	2.62*	0.16	0.46**	0.35	4.35	3.25
Switzerland	3.69***	2.13*	0.18	0.47**	0.34	3.91	2.34
United Kingdom	3.06***	1.88*	0.01	0.49***	0.28	3.18	1.99
United States	2.97**	1.66	0.13	0.42**	0.40	2.97	1.63
Cross-country Investment							
Cross-country	3.64**	2.05*	0.12	0.40***	0.31	3.55	2.33

Table VI: **Out-of-sample forecasting performance and volatility spillover intensity**

The table reports the out-of-sample forecasting results of the U.S forward variance risk factor during four subperiods. Specifically, the second (third) column repors the subsample R^2_{OS} statistics during periods of high (low) intensity of U.S. volatility spillover. The fourth (fifth) column reports the R^2_{OS} statistics computed for the periods in which the global connectedness is high (low). The subsample R^2_{OS} statistic is defined as

$$R^2_{OS,c} = 1 - \frac{\sum_{t=H}^{T-1} I^c_{t+1}(R^i_{t+1} - \hat{R}^i_{t+1})^2}{\sum_{t=H}^{T-1} I^c_{t+1}(R^i_{t+1} - \bar{R}^i_{t+1})^2}, \text{ for } c = high,\ low,$$

where I^{high}_{t+1} (I^{low}_{t+1}) is set equal to one whenever the volatility spillover from the U.S. to the other country or the global connectedness is above (below) its full-sample mean level in month $t+1$, and zero otherwise. We use the Clark and West (2007) MSFE-adjusted statistic that tests the null hypothesis $R^2_{OS} \leq 0$ against the alternative $R^2_{OS} > 0$ to assess the significance of R^2_{OS} values. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from March 2001 to June 2019.

(1)	(2)	(3)	(4)	(5)
	Subsample by: U.S. Volatility Spillover Intensity		**Subsample by: Global Connectedness**	
	High	Low	High	Low
Australia	1.61*	0.27	1.38*	0.74
Canada	1.89*	0.32	1.49*	0.94
France	4.41**	2.12	3.47**	3.75**
Germany	3.52**	1.78	2.94**	2.77*
Italy	3.91**	0.97	2.91**	2.68**
Japan	−1.08	1.37***	−1.15	1.48***
Netherlands	2.96**	1.64	2.39**	2.89*
Sweden	4.12**	1.55	3.89**	1.52
Switzerland	5.60**	2.39*	5.18**	2.85*
United Kingdom	2.60*	0.38	2.18	0.93

Table VII: **Predicting U.S. economic conditions**

The table reports the estimated slope coefficient, t-statistic, and R^2 statistic of the following predictive regression

$$y^j_{t+1} = \alpha^j + \beta^j(\text{U.S. FVs})^{\text{PLS}}_t + \varepsilon^j_t$$

where y^j_{t+1} is one of the U.S. economic condition measures in month $t+1$, and $(\text{U.S. FVs})^{\text{PLS}}_t$ is the PLS factor in month t extracted from the set of U.S. forward variances (FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m}) using y^j as the target variable. The t-statistic is calculated following Kelly and Pruitt (2015). The U.S. economic condition measures are in monthly frequency, including the NBER recession indicator (NBER), Chicago Fed National Activity Index (CFNAI), Kansas City Financial Stress Index (KCFSI), Industrial Production Growth in percentage (IPG (%)), Nonfarm Payroll Growth in percentage (Payroll (%)), Smooth Recession Probability (SRP), Aruoba et al. (2009) Business Conditions Index (ADS). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from February 1996 to June 2019.

(1)	(2) $\boldsymbol{\beta}$	(3) $\boldsymbol{t}$**-stat**	(4) $\boldsymbol{R^2}$**(%)**
NBER	0.09	4.37***	9.61
CFNAI	−0.10	−1.82*	3.73
KCFSI	0.35	3.31***	10.34
IPG(%)	−0.10	−1.91*	2.25
Payroll(%)	−0.04	−2.83***	7.44
SRP	0.07	3.73***	10.37
ADS	−0.14	−2.06**	4.51

Table VIII: **Predicting international economic conditions**

Panels A and B of the table presents the forecasting results for local industrial production growth (IPG, in percent) and economic policy uncertainty (EPU) index, respectively, using U.S. forward variances. The second through fourth columns report the estimated slope coefficient, t-statistic, and R^2 statistic of the following univariate predictive regression,

$$y_{i,t+1} = \alpha_i + \beta_i(\text{U.S. FVs})_{i,t}^{\text{PLS}} + \varepsilon_{i,t+1}, \quad y = \text{IPG, EPU},$$

where $y_{i,t+1}$ is the IPG/EPU of country i in month $t+1$, and $(\text{U.S. FVs})_{i,t}^{\text{PLS}}$ is the tth month PLS factor extracted from the set of U.S. forward variances (FV_{3m6m}, FV_{6m9m}, FV_{9m12m}, and FV_{12m18m}) using $y_{i,t+1}$ as the target variable. The fifth through ninth columns report the estimated slope coefficients, t-statistic, and R^2 statistic of the following bivariate predictive regression,

$$y_{i,t+1} = \alpha_i + \beta_i(\text{U.S. FVs})_{i,t}^{\text{PLS}} + \gamma_i y_{i,t} + \varepsilon_{i,t+1}, \quad y = \text{IPG, EPU},$$

where $y_{i,t}$ is the lagged IPG/EPU of country i. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The IPG sample period ranges from February 1996 to June 2019 for all countries except for Australia (February 1996 to March 2016). The EPU sample period ranges from February 1996 to June 2019 for Canada, France, Germany, Japan, Sweden and the United States, and from January 1997 to June 2019 for Australia, Italy, the Netherlands, and the United Kingdom.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Univariate regression			**Bivariate regression**				
	β	t-stat	$R^2(\%)$	β	t-stat	γ	t-stat	$R^2(\%)$
Panel A: ***predicting industrial production growth***								
Australia	0.20	4.31***	1.12	0.05	1.93*	0.87	5.28***	76.60
Canada	−0.07	−2.83***	3.56	−0.02	−2.24**	0.88	26.19***	79.85
France	−0.07	−2.05**	3.99	−0.01	−0.54	0.83	19.23***	70.45
Germany	−0.13	−3.34***	7.64	−0.03	−1.90*	0.88	25.49***	79.70
Italy	−0.10	−2.23**	4.32	−0.03	−1.88*	0.89	26.01***	81.80
Japan	−0.20	−3.49***	8.16	−0.04	−1.67*	0.88	21.54***	79.88
Netherlands	−0.04	−1.67*	1.32	−0.02	−1.05	0.64	10.87***	42.18
Sweden	−0.11	−2.44**	2.98	−0.06	−2.29**	0.70	9.96***	51.49
Switzerland	-	-	-	-	-	-	-	-
United Kingdom	−0.05	−2.48**	4.63	−0.02	−1.77*	0.73	12.75***	56.87
Panel B: ***predicting economic policy uncertainty***								
Australia	12.93	2.43**	5.19	5.55	2.25**	0.66	10.58***	47.27
Canada	24.34	3.73***	7.80	6.43	2.94***	0.83	24.61***	70.95
France	44.79	5.83***	19.20	8.16	2.16**	0.78	15.12***	67.39
Germany	17.08	3.68***	7.53	7.65	2.93***	0.60	15.88***	41.35
Italy	6.51	1.89*	2.86	1.80	0.67	0.59	10.65***	36.20
Japan	2.66	1.04	0.55	1.31	0.95	0.78	15.07***	60.36
Netherlands	4.30	1.35	1.39	0.61	0.36	0.65	13.27***	42.53
Sweden	1.99	1.30	1.14	2.32	2.77***	0.65	13.67***	43.93
Switzerland	-	-	-	-	-	-	-	-
United Kingdom	53.29	5.53***	12.13	7.54	1.76*	0.85	9.24***	75.42

Table IX: **Predicting Googling investor sentiment index**

The table shows the forecasting results for the googling investor sentiment of Gao et al. (2020). We report the estimated slope coefficient, t-statistic, and R^2 statistic of the following predictive regression,

$$\text{SENTI}_{i,t+1} = \alpha_i + \beta_i(\text{U.S. FVs})^{\text{PLS}}_{i,t} + \gamma_i \text{SENTI}_{i,t} + \varepsilon_{i,t+1},$$

where $\text{SENTI}_{i,t+1}$ is the googling investor sentiment of country i in month $t+1$, and $(\text{U.S. FVs})^{\text{PLS}}_{i,t}$ is the extracted PLS factor using $\text{SENTI}_{i,t+1}$ as the target variable. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from July 2004 to December 2014.

(1)	(2) $\beta(\%)$	(3) t-stat	(4) γ	(5) t-stat	(6) $R^2(\%)$
Australia	1.68	1.04	−0.33	−4.40***	11.65
Canada	1.20	0.50	−0.44	−6.77***	19.61
France	1.36	0.77	−0.24	−2.71***	5.92
Germany	1.62	0.38	−0.41	−5.90***	16.46
Italy	−4.59	−1.57	−0.31	−3.44***	10.21
Japan	6.68	2.98***	−0.40	−4.32***	20.33
Netherlands	3.60	1.38	−0.34	−4.27***	12.58
Sweden	6.29	2.39**	−0.32	−3.73***	13.23
Switzerland	11.15	2.83***	−0.40	−5.15***	18.56
United Kingdom	−0.80	−0.62	−0.49	−6.89***	24.37
United States	2.93	1.50	−0.25	−2.99***	8.16

Table X: **Predicting U.S. dollar-denominated stock returns**

This table reports the estimation results of the following predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_t^{\mathrm{US}} + \varepsilon_{i,t+1}$$

where r_i is the excess log market return denominated in the U.S. dollar of country i and $\mathrm{FVF}^{\mathrm{US}}$ is the U.S. forward variance risk factor. $\mathrm{FVF}^{\mathrm{US}}$ is standardized to have zero mean and unit variance. We report regression estimate of β_i (in percent), the associated t-statistic following Kelly and Pruitt (2015), and R^2 statistic for each regression. The fifth and sixth columns report the subsample R^2 statistics over NBER-dated business cycle recessions (R^2_{Rec}) and expansions (R^2_{Exp}). The last row presents the pooled OLS regression estimates where the restriction that β_is are the same for all countries is imposed. The t-statistics of pooled estimates are based on the GMM, following Ang and Bekaert (2007). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from February 1996 to June 2019.

(1)	(2) $\boldsymbol{\beta}$**(%)**	(3) ***t*-stat**	(4) $\boldsymbol{R^2}$**(%)**	(5) $\boldsymbol{R^2_{Rec}}$**(%)**	(6) $\boldsymbol{R^2_{Exp}}$**(%)**
Australia	0.61	1.72*	1.01	2.61	0.26
Canada	0.57	1.99**	0.94	1.78	0.63
France	0.85	2.42**	2.12	4.64	1.19
Germany	0.88	2.25**	1.84	4.54	0.86
Italy	0.77	2.60***	1.30	3.57	0.65
Japan	0.36	0.66	0.52	1.93	0.22
Netherlands	0.78	2.34**	1.69	3.51	0.88
Sweden	0.75	1.86*	1.22	3.14	0.48
Switzerland	0.92	3.01***	3.82	5.58	3.39
United Kingdom	0.70	2.71***	2.30	4.67	1.35
United States	0.68	2.53**	2.44	4.98	1.58
Pooled	0.71	2.43**	1.64		

Table XI: **Country-specific forward variance risk factor**

This table shows the estimation results of the following predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \,\mathrm{FVF}_{i,t}^{\mathrm{US}} + \varepsilon_{i,t+1}$$

where r_i is the excess log market return of country i and $\mathrm{FVF}_i^{\mathrm{US}}$ is the country-specific forward variance risk factor for country i that is extracted from U.S. forward variances by PLS using r_i as the target variable. The factor $\mathrm{FVF}_i^{\mathrm{US}}$ is standardized to have zero mean and unit variance. Stock returns are denominated in domestic currencies. The second through fourth columns report the regression slope estimates (in percentage), the associated t-statistics, and the regression R^2 statistics are reported. The t-statistics are calculated following Kelly and Pruitt (2015). The fifth and sixth columns report the subsample R^2 statistics over NBER-dated business cycle recessions (R^2_{Rec}) and expansions (R^2_{Exp}), respectively. The seventh column reports the OOS R^2 statistics. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The in-sample estimation period ranges from February 1996 to June 2019, and the OOS period ranges from February 2001 to June 2019.

(1)	(2) β(%)	(3) t-stat	(4) R^2(%)	(5) R^2_{Rec}(%)	(6) R^2_{Exp}(%)	(7) R^2_{OS}(%)
Australia	−0.48	−1.63	1.75	6.85	−0.40	1.29**
Canada	0.52	2.00**	1.52	3.23	0.96	1.61**
France	1.02	2.86***	3.95	10.84	1.86	4.47***
Germany	1.04	2.51**	3.16	9.65	1.32	3.57***
Italy	0.92	2.96***	2.40	7.97	1.03	2.44**
Japan	0.46	1.31	0.82	1.77	0.56	−0.52
Netherlands	0.95	2.81***	3.16	7.46	1.51	3.65***
Sweden	0.94	2.43**	2.73	7.85	1.12	2.81**
Switzerland	−1.08	−3.77***	6.26	15.31	4.20	7.03***
United Kingdom	0.67	2.84**	2.98	6.30	1.89	2.64**

Table XII: **Return predictability over subsamples**

This table shows the estimation results of the following predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_t^{\mathrm{US}} + \varepsilon_{i,t+1}$$

where r_i is the excess log market return of emerging market i and $\mathrm{FVF}^{\mathrm{US}}$ is the U.S. forward variance risk factor. $\mathrm{FVF}^{\mathrm{US}}$ is standardized to have zero mean and unit variance. We report the regression estimate of β_i (in percent), the associated t-statistic following Kelly and Pruitt (2015), and R^2 statistic for each regression. We consider three subsample periods, from February 1996 to October 2007, from November 2007 to June 2019, and from February 1996 to June 2019 excluding for observations during 2008 recession (from January 2008 to June 2009). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1996:02-2007:10			**2007:11-2019:06**			**exclude 2008 recession**		
	β(%)	t-stat	R^2(%)	β(%)	t-stat	R^2(%)	β(%)	t-stat	R^2(%)
Australia	0.16	0.69	0.24	1.10	3.14***	7.19	0.27	1.24	0.67
Canada	0.53	1.33	1.36	0.63	2.62***	2.69	0.43	1.62	1.23
France	0.75	2.34**	1.99	1.63	4.80***	10.81	0.68	2.39**	1.99
Germany	0.69	2.11**	1.24	1.82	4.48***	11.15	0.66	2.11**	1.45
Italy	0.68	2.06**	1.27	1.36	3.91***	5.36	0.69	2.56**	1.48
Japan	−0.49	−1.45	1.08	1.55	4.44***	7.93	−0.01	−0.03	0.00
Netherlands	0.49	1.90*	0.78	1.67	4.66***	10.62	0.55	2.41**	1.30
Sweden	0.84	2.25**	1.82	1.20	2.91***	5.72	0.68	2.13**	1.63
Switzerland	0.76	2.14**	2.56	1.48	7.22***	14.96	0.72	2.89***	3.02
United Kingdom	0.62	2.70***	2.64	0.95	3.43***	5.56	0.51	2.46**	1.97
United States	0.82	3.21***	3.74	1.06	3.49***	5.72	0.58	2.23**	2.09

Table XIII: **Predicting emerging markets stock returns**

This table shows the estimation results of the following predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_t^{\mathrm{US}} + \varepsilon_{i,t+1}$$

where r_i is the excess log market return of emerging market i and $\mathrm{FVF}^{\mathrm{US}}$ is the U.S. forward variance risk factor. $\mathrm{FVF}^{\mathrm{US}}$ is standardized to have zero mean and unit variance. We report the regression estimate of β_i (in percent), the associated t-statistic following Kelly and Pruitt (2015), and R^2 statistic for each regression. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample periods are from February 1996 to June 2019 for Greece, Hungary, Poland, South Africa, Brazil, Mexico, India, Malaysia, Pakistan, Philippines, and Taiwan, from February 1998 to June 2019 for Colombia, February 2002 to June 2019 for China, and February 1997 to June 2019 for Thailand.

(1)	(2) $\beta(\%)$	(3) t-stat	(4) $R^2(\%)$	(5)	(6) $\beta(\%)$	(7) t-stat	(8) $R^2(\%)$
Greece	0.51	0.96	0.30	China	0.43	0.69	0.30
Hungary	0.43	0.83	0.31	India	−0.63	−1.28	0.86
Poland	0.04	0.09	0.00	Malaysia	0.49	0.69	0.52
South Africa	0.56	1.31	1.10	Pakistan	−1.00	−0.95	0.96
Brazil	0.50	1.16	0.37	Philippines	0.86	1.56	1.71
Colombia	0.83	1.24	1.23	Taiwan	−0.07	−0.10	0.01
Mexico	0.36	1.00	0.37	Thailand	0.92	1.15	1.06

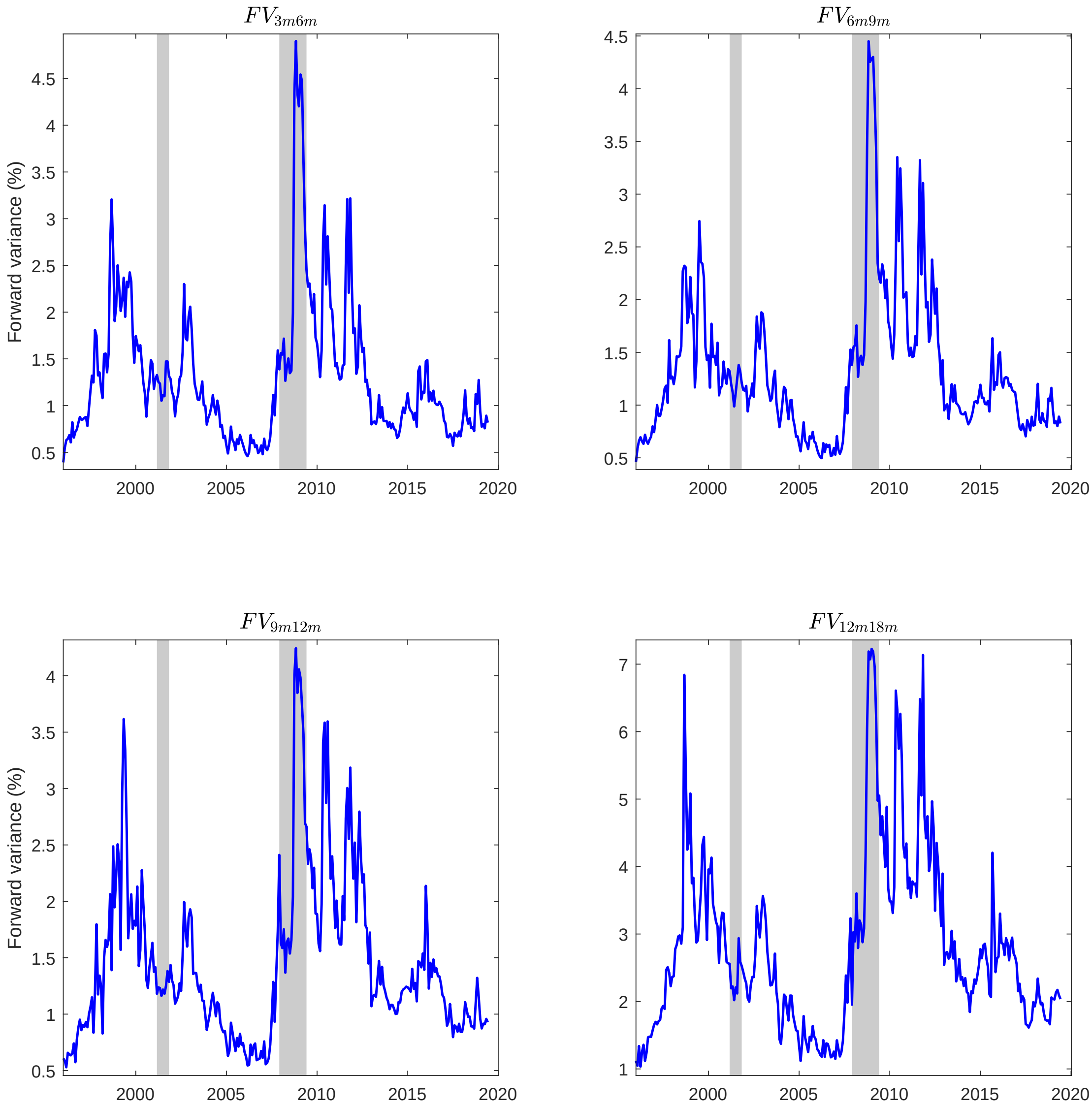

Figure 1: **The term structure of U.S. forward variances**

The figure depicts the dynamics of the term structure of the U.S. risk-neutral forward variances, which are the risk neutral variances of the S&P 500 index return over three to six (FV_{3m6m}), six to nine (FV_{6m9m}), nine to twelve (FV_{9m12m}), and twelve to eighteen (FV_{12m18m}) months ahead. The shaded area corresponds to the NBER recession period. The sample period ranges from January 1996 to June 2019.

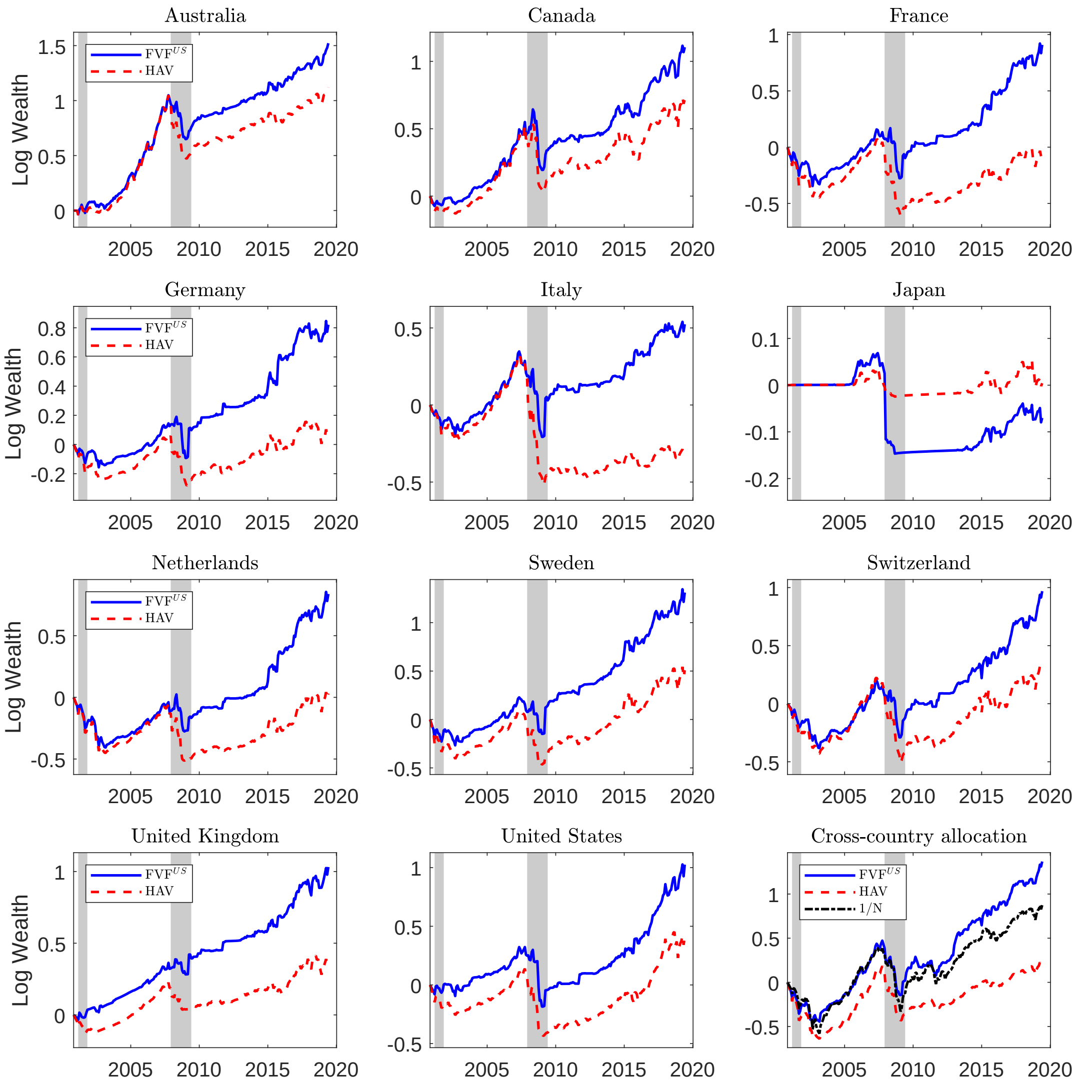

Figure 2: **Out-of-sample asset allocation performance: log cumulative wealth**
The figure depicts the log cumulative wealth for a mean-variance investor with a relative risk aversion coefficient of five who allocates monthly between the treasury bill and the stock market index using excess market return forecasts based on the U.S. forward variance risk factor FVF$^{\mathrm{US}}$ (solid line) or the historical mean forecasts (dashed line). The first 11 subplots consider an investor who invests in the entitled country only, and the last subplot consider a cross-country investment strategy. Stock returns are denominated in domestic currencies. The shaded area corresponds to the U.S. recession periods dated by the NBER. The out-of-sample period ranges from February 2001 to June 2019.

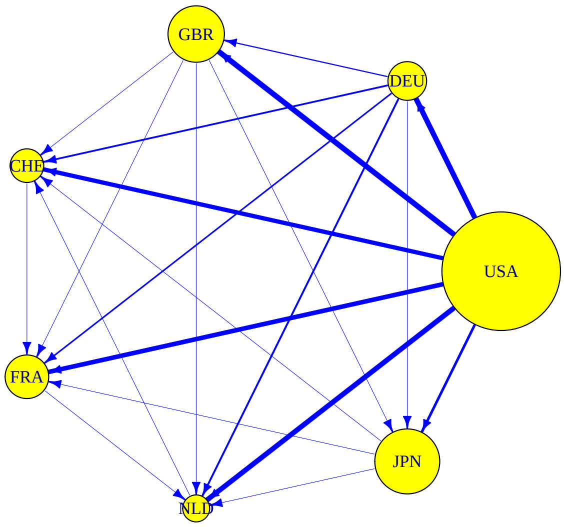

Figure 3: **Static Net Volatility Spillover Network**

The figure plots the net volatility spillover (contribution to the other countries minus contribution received) among the seven countries, including the United States (USA), Germany (DEU), the United Kingdom (GBR), Switzerland (CHE), France (FRA), the Netherlands (NLD), and Japan (JPA). Following Diebold and Yilmaz (2009), we perform the variance decomposition using a VAR of order four with a predictive horizon of four weeks. Node size indicates stock market capitalization. Edge width indicates magnitude of the volatility spillover. The analysis is based on the first differences in the weekly VIX series of each country ranging from January 2000 to June 2019.

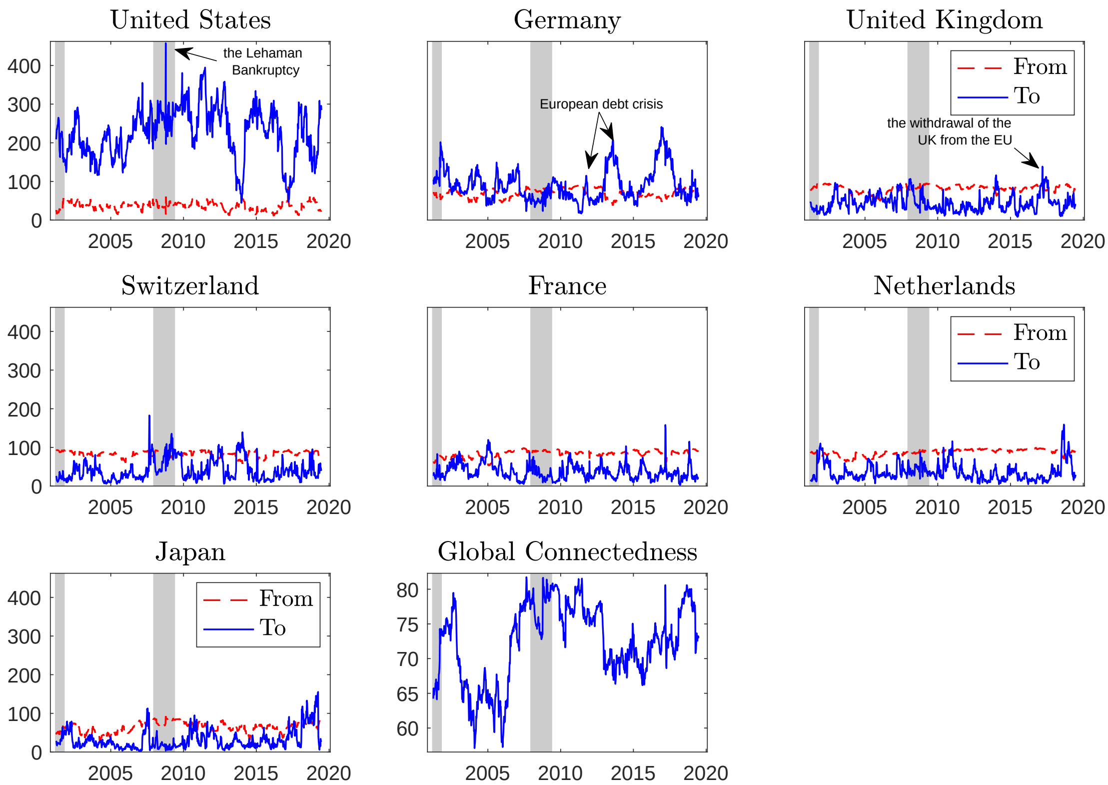

Figure 4: **Dynamic Spillover Plot**

The figure plots time variations in the volatility spillover of each country and the global connectedness. The variance decomposition is based on a VAR of order four using the first differences in the weekly VIX series of each country. The rolling estimation window width is 60 weeks, and the predictive horizon is four weeks. In the first seven subplots, the solid line depicts the sum of estimated contributions to the variance of the other countries coming from the entitled country, and the dashed line depicts the sum of estimated contributions to the variance of the entitled country coming from the other countries. The last subplot shows the rolling estimated global connectedness. The shaded area corresponds to the U.S. recession periods dated by the NBER. The sample period ranges from March 2001 to June 2019..

Internet Appendix

A Measures of the U.S. macroeconomic conditions

- **NBER**: A dummy variables that equals one if the U.S. economy is in a recession dated by the NBER and zero otherwise. The data are obtained from the Federal Reserve Bank (FRB) of St. Louis.
- **Chicago Fed National Activity Index (CFNAI)**: The CFNAI is a monthly index that measures the aggregate U.S. economic activity and also captures the inflationary pressure. It is a weighted average of 85 monthly macroeconomic indicators. A positive (negative) value of the index reflects that the U.S. economy activity is above (below) the historical trend. The data are obtained from the FRB of Chicago.
- **Kansas City Financial Stress Index (KCFSI)**: The KCFSI is a monthly measure that assess the level of the U.S. financial system stress based on 11 financial market variables. A positive value of the index indicates that financial stress is above the long-run average, while a negative value signifies that financial stress is below the long-run average. The data are from the FRB of Kansas City.
- **Industrial Production Growth (IPG)**: The growth rate of the monthly U.S. total industrial production index. The data are from the FRB of St. Louis.
- **Nonfarm Payroll Growth (Payroll)**: The growth rate of the monthly U.S. non-farm payroll. The data are from the U.S. Bureau of Labor Statistics.
- **Smoothed Recession Probability (SRP)**: The monthly U.S. smoothed recession probabilities are calculated from a dynamic-factor Markov-switching model by Chauvet (1998), applied to four monthly coincident variables: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. The data are from the FRB of St. Louis.
- **Aruoba-Diebold-Scotti Business Conditions Index (ADS)**: The index is designed to track U.S. real business conditions at a high observation frequency using six seasonally adjusted economic indicators are weekly, monthly and quarterly frequency. A series of positive values of the index indicates that the U.S. economy is in a better-than-average track, whereas a series of negative values of the index reflects the opposite. The ADS index data are obtained from the FRB of Philadelphia.

Table A.1: **Stock return indices for international countries**

The table shows the stock market indices of the eleven industrialized countries used in the main empirical analyse. All the indices are total return indices that include the dividend payments, and provide a broad coverage of the underlying stock markets in terms of capitalizations. The data are from the Global Financial Database (GFD). The last column reports the tickers of the GFD.

Country	**Stock market index**	**GFD Ticker**
Australia	Australia ASX Accumulation Index	AORDAD
Canada	Canada S&P/TSX-300 Total Return Index	TRGSPTSE
France	France CAC All-Tradable Total Return Index	TRSBF250D
Germany	Germany CDAX Total Return Index	CDAXD
Italy	Italy BCI Global Return Index	BCIPRD
Japan	Japan Topix Total Return Index	TOPXDVD
Netherlands	Netherlands All-Share Return Index	AAXGRD
Sweden	OMX Stockholm Benchmark Gross Index	OMXSBGI
Switzerland	Swiss Performance Index	SSHID
United Kingdom	UK FTSE All-Share Return Index	TFTASD
United States	S&P 500 Total Return Index	SPXTRD

Table A.2: **In-sample estimation results: Control for local VIX index**

This table shows estimation results of the in-sample predictive regression,

$$r_{i,t+1} = \alpha_i + \beta_i \, \mathrm{FVF}_t^{\mathrm{US}} + \gamma_i \mathrm{VIX}_{i,t}^2 + \varepsilon_{i,t+1}$$

where r_i is the excess log market return of country i, $\mathrm{FVF}^{\mathrm{US}}$ is the U.S. forward variance risk factor, and VIX_i^2 is the squared VIX index for country i. Stock returns are denominated in domestic currencies. All predictive variables are standardized to have zero mean and unit variance. We report the regression coefficients (in percent), the associated Newey-West t-statistics, and the R^2 statistic for each predictive regression. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The last column shows the sample period for each regression.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FVF$^{\mathrm{US}}$		**VIX^2**			
Country	β(%)	t-stat	β(%)	t-stat	R^2(%)	Sample Period
Australia	0.45	1.47	−0.64	−1.15	4.95	2008:01-2019:06
Canada	0.62	2.13**	0.42	1.37	7.92	2010:10-2019:06
France	1.28	3.84***	0.32	0.65	6.19	2000:01-2019:06
Germany	1.07	2.55**	−0.25	−0.52	3.40	1996:01-2019:06
Italy	-	-	-	-	-	
Japan	0.34	0.83	−0.32	−1.30	0.84	1996:01-2019:06
Netherlands	1.23	3.29***	0.07	0.13	5.36	2000:01-2019:06
Sweden	0.75	1.42	0.00	0.00	2.60	2004:05-2018:09
Switzerland	0.89	2.63***	−0.36	−1.14	6.86	1999:01-2019:06
United Kingdom	0.67	2.43**	0.13	0.35	2.72	2000:01-2019:06
United States	0.68	2.58***	−0.03	−0.07	2.44	1996:01-2019:06

Table A.3: **Predicting U.S. dollar-denominated stock returns: multivariate analysis**

The table shows the results controlling for local economic conditions, local volatility risk, and alternative U.S. predictive variables. Panel A reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{TBL}_{i,t} + \beta_{i,3}\mathrm{DY}_{i,t} + \beta_{i,4}\mathrm{TMS}_{i,t} + \beta_{i,5}\mathrm{Jan}_{t+1} + \varepsilon_{i,t+1}$$

where r_i is the excess log market return of country i, FVF_t^{US} is the U.S. forward variance risk factor, TBL_i is the three-month treasury bill rate of country i, DY_i is the dividend yield of country i, TMS_i is the term spread, and Jan is the January dummy. Panel B reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{SVAR}_{i,t} + \varepsilon_{i,t+1}$$

where $\mathrm{SVAR}_{i,t}$ is the stock variance of country i. Panel C reports the estimation results for the predictive regression model,

$$r_{i,t+1} = \alpha_i + \beta_{i,1}\,\mathrm{FVF}_t^{\mathrm{US}} + \beta_{i,2}\mathrm{SKEW}_t^{\mathrm{US}} + \beta_{i,3}\mathrm{VRP}_t^{\mathrm{US}} + \beta_{i,4}r_{\mathrm{US},t} + \varepsilon_{i,t+1}$$

where $\mathrm{SKEW}^{\mathrm{US}}$ is the monthly innovations in U.S. stock market skewness, VRP^{US} is the U.S. variance risk premium of Bollerslev et al. (2009), and r_{US} is the lagged U.S. market return. The coefficient estimates (in percentage), the associated Newey-West t-statistics, and the R^2 of each regression are reported. The last row of each Panel reports the pooled OLS estimates where the restriction that β^is are the same for all countries is imposed. The t-statistics of pooled estimates are based on the GMM, following Ang and Bekaert (2007). Stock returns are denominated in the U.S. dollar. All predictive variables are standardized to have zero mean and unit variance. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. The sample period ranges from February 1996 to June 2019.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: controlling for local financial and economic variables											
	$\mathrm{FVF}^{\mathrm{US}}$		**TBL**		**DY**		**TMS**		**Jan**		
	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	β(%)	t-stat	R^2(%)
Australia	0.59	1.74*	0.20	0.36	0.58	0.79	0.69	1.56	−0.73	−0.53	2.97
Canada	0.58	1.88*	0.06	0.10	0.19	0.22	0.46	1.04	0.31	0.29	1.55
France	0.83	2.20**	−0.42	−0.99	−0.16	−0.28	0.70	1.91*	−1.06	−0.84	4.42
Germany	0.87	2.41**	−0.91	−1.66	−0.46	−0.66	0.84	2.15**	−1.07	−0.75	5.13
Italy	0.77	2.75***	0.04	0.07	−0.41	−0.54	0.36	0.62	0.22	0.16	1.60
Japan	0.35	0.57	−1.02	−2.69***	0.56	0.95	0.49	0.87	−0.59	−0.52	4.80
Netherlands	0.74	2.40**	−0.57	−1.75	−0.02	−0.04	0.91	1.89*	−1.67	−1.48	6.23
Sweden	0.82	1.83*	−0.25	−0.54	0.74	1.17	1.84	3.66***	−0.51	−0.36	8.03
Switzerland	0.89	2.89***	−0.84	−1.70*	−0.38	−0.58	0.44	1.01	−1.31	−1.19	7.96
United Kingdom	0.66	2.44**	0.21	0.65	0.23	0.44	0.49	1.33	−1.41	−1.51	4.26
United States	0.62	2.16**	−0.07	−0.17	0.62	1.35	−0.37	−0.99	−0.31	−0.34	4.50
Pooled	0.70	2.42**	−0.34	−1.03	0.03	0.08	0.45	2.32**	−0.74	−0.72	3.00

Panel B: controlling for local volatility risk					
	$\mathrm{FVF}^{\mathrm{US}}$		**SVAR**		
	β(%)	t-stat	β(%)	t-stat	R^2(%)
Australia	0.61	1.78*	−0.40	−0.71	1.44
Canada	0.56	1.86*	−0.88	−1.88*	3.19
France	0.88	2.20**	−0.34	−0.76	2.46
Germany	0.88	2.20**	−0.07	−0.13	1.85
Italy	0.77	2.68***	−0.01	−0.02	1.30
Japan	0.37	0.60	0.20	0.86	0.68
Netherlands	0.81	2.27**	−0.36	−0.72	2.06
Sweden	0.77	1.74*	−0.28	−0.51	1.39
Switzerland	0.96	2.68***	−0.47	−1.54	4.83
United Kingdom	0.70	2.58***	−0.52	−1.37	3.57
United States	0.68	2.54**	−0.64	−1.79*	4.58
Pooled	0.73	2.49**	−0.34	−0.90	1.98

Panel C: controlling for alternative U.S. predictors	**FVF$^{\text{US}}$**		**SKEW$^{\text{US}}$**		**VRP$^{\text{US}}$**		**lagged US Return**		
	$\beta(\%)$	t-stat	$\beta(\%)$	t-stat	$\beta(\%)$	t-stat	$\beta(\%)$	t-stat	$R^2(\%)$
Australia	0.45	1.32	0.24	0.82	1.21	3.32***	0.13	0.27	5.37
Canada	0.37	1.31	0.44	1.57	0.74	2.16**	0.70	1.45	4.67
France	0.72	1.86*	0.67	2.23**	0.57	1.48	0.41	0.88	4.93
Germany	0.73	1.78*	0.56	1.72*	0.67	1.82*	0.46	0.93	4.26
Italy	0.64	2.13**	0.48	1.36	0.47	1.26	0.47	0.89	2.77
Japan	0.32	0.50	0.45	1.86*	−0.34	−1.37	0.54	1.56	2.18
Netherlands	0.65	1.71*	0.63	2.13**	0.26	0.70	0.65	1.21	3.85
Sweden	0.62	1.40	0.46	1.49	0.71	1.51	0.31	0.56	3.11
Switzerland	0.82	2.55**	0.43	1.78*	0.30	0.87	0.39	1.08	5.70
United Kingdom	0.56	2.03**	0.41	1.67*	0.54	1.90*	0.50	1.33	5.74
United States	0.54	2.25**	0.21	1.05	0.87	3.50***	0.23	0.74	7.28
Pooled	0.58	1.95*	0.45	1.97**	0.54	1.75*	0.44	0.96	3.80