Variance Risk Premiums in Emerging Markets*

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We construct variance risk premiums for 9 major emerging markets, Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan, from 2000 to 2017, using the sample-extension methodology of Lynch and Wachter (2013). Both the emerging market and developed market variance risk premiums can predict stock returns, currency returns, and capital inflows, while the former is more important for longer horizons, and the latter is more important for shorter horizons. This finding suggests that the variance risk premium is important in emerging markets finance, and the emerging market variance risk premium might capture risks not embedded in the developed market one.

JEL Classification: G12, G13, G15.
Keywords: GMM, variance risk premium, emerging markets, predictability, stock returns, currency returns, and capital inflows.

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1 Introduction

The variance risk premium (VRP) is the difference between the risk-neutral and physical expectations of the future return variance. A number of recent studies, such as Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011), argue that the VRP is an important state variable measuring economic uncertainty. As a state variable, the VRP contains information about future investment opportunity set, and should predict future economic conditions, such as stock market returns and currency returns. Earlier studies, such as Bollerslev, Marrone, Xu, and Zhou (2014) and Londono and Zhou (2017), show that the VRP successfully predicts stock market index returns and currency returns in the U.S. and developed markets.

Globalization has been marked by the rapid and dramatic economic growth in emerging markets. In late 2017, the emerging markets' GDP accounts for more than 30% of the global GDP, and in terms of stock market capitalization, emerging markets now account for more than 18%. Despite the importance of emerging economies and their financial markets, little research on the VRP has been conducted for emerging markets, due to the short length of the option-implied volatility data. In this paper, we fill the gap in the literature and construct the VRPs in emerging markets from 2000 to 2017, to study its predictive power for important economic variables.

We adopt the econometric methodology in Lynch and Wachter (2013) to extend the option-implied variance in 9 major emerging markets (Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan) back to January 2000.[1] Following Carr and Madan (1998), Britten-Jones and Neuberger (2000), and Jiang and Tian (2005), the implied variance is calculated from option prices without the use of any particular option-pricing model. As in Andersen and Bollerslev (1998) and Andersen, Bollerslev, Diebold, and Labys (2003), we compute the realized variance by summing squared daily returns over one month. The VRP measure is the difference between the option-implied variance and the conditional

[1] Earlier work includes Anderson (1957) and Stambaugh (1997), which derive estimates of the mean, variance, and the posterior distribution of returns, in a setting where some return series began on a later date than others. Barras and Malkhozov (2016) apply the Lynch and Wachter (2013) method to extend the option-implied volatility in the U.S. stock market.

expectation of the future realized variance.

For all 9 emerging markets, we calculate individual local country-level VRPs, and our extended VRP measure successfully matches major narrative events. To capture the commonality among VRPs from emerging markets, we compute an emerging market VRP as the market capitalization weighted average of all the emerging market country-level VRPs. To find the difference between emerging markets and developed markets, we also construct individual local country-level VRPs for 11 developed markets (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S.), as well as a developed market VRP as the market capitalization weighted average of all developed market country-level VRPs. Finally, a global VRP is computed as the market capitalization weighted average of all the country-level VRPs. The separation among local and global, developed market and emerging market VRPs allows us to compare the different information content in each of them and shed light on market integration issues, as discussed in Bekaert and Harvey (2014).

We first examine whether VRPs can predict market stock index returns in emerging markets. The global VRP, as a proxy for world aggregate systematic risk or economic uncertainty, shows significant and stronger return predictability than country-level VRPs over all forecasting horizons, indicating that emerging market equity returns are more influenced by the global VRP than their own country-level VRPs. In fact, the predicting power of country-level VRPs disappears if we include the global VRP. Both the developed market VRP, which is highly correlated with the global VRP, and the emerging market VRP significantly predict stock returns. Interestingly, the developed market VRP manifests itself as a predictor in the short run (1- to 4-month), while the emerging market VRP dominates return predictability beyond the 4-month horizon. The joint return predictability of the developed market and emerging market VRPs is, in general, stronger than the global VRP alone over all horizons.

We further examine the predictive power of the VRPs for two other important economic variables—currency returns and capital flows. The forward premium puzzle and the resulting currency return predictability have been well documented in the literature, such as Hansen and Hodrick (1980) and Fama (1984). The predictive patterns of global, developed market, and emerging market VRPs for foreign currency returns (with respect to the U.S. dollar) in emerging markets are quite similar to those for stock market return predictions. The global and developed market VRPs have strong and positive predictive power for foreign currency returns over the shorter horizon. The emerging market VRP has higher predictive power than the developed market VRP over the longer horizon. Meanwhile, the capital inflows to emerging markets, an important source to accelerate the local economic growth, may also be predictable by market risk factors, as in Rey (2015) and Forbes and Warnock (2012). We provide novel empirical evidence that increases in lagged global, developed market, and emerging market VRPs can all lead to an increase in net capital inflows scaled by GDP. The developed market VRP is significant over 2 quarters, while the emerging market VRP is more important for longer horizons.

The focus of our paper is to construct the long time series of the VRP measures, and document their strong predictive power, which we show above. We also briefly look into the question of what drives the different predictive patterns of the developed market and emerging market VRPs. We find that the emerging market VRP is more correlated with the volatility of GDP growth, which reflects cash flow uncertainty, while the developed market VRP is more correlated with the volatility of interest rates, which measures discount rate uncertainty. Therefore, the distinctive predictive patterns of the emerging market and developed market VRPs are driven by different information contained in these two VRP measures.

Our new empirical findings contribute to the literature in several perspectives. Our first contribution is that we extend VRPs in emerging markets by 10+ years, which provides a measure of economic uncertainty in emerging markets over the sample period from January 2000 to October 2017.[2] The relatively long time series of VRP data can be used in many areas of finance.

Second, while the short-run return predictability patterns afforded by the VRP have been documented in major developed stock markets (see Bollerslev, Tauchen, and Zhou,

[2] Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), and Drechsler (2013) relate the VRP to economic uncertainty risk.

2009, Bollerslev, Marrone, Xu, and Zhou, 2014, and Londono, 2015, among others), our paper further extends the scope and studies the return predictability of the VRP in major emerging markets.[3] Not only we confirm the previous studies' findings that the developed market VRP has strong predictive power for stock returns over shorter horizons, we also have novel findings that the emerging market VRP has strong predictive power for stock returns, currency returns, and capital flows over longer horizons, which indicates that our new emerging market VRP contains different information from the developed market VRP. The developed market VRP is highly correlated with the global VRP, and maybe it is easy to interpret it as the global risk premium. The strong and different predictive power of the emerging market VRP indicates that there is different risk generated from emerging markets, and yet is important for all markets. We also find that the global VRP has stronger predictive power than the country-specific VRP in emerging markets. It shows that emerging markets have at least partially integrated in the global capital market, with global uncertainties being more important than country-specific uncertainties.

The remainder of this paper is organized as follows. In Section 2, we extend the samples of VRPs for emerging markets. We use VRP measures to predict important financial variables in Section 3. Section 4 provides many robustness checks. Section 5 concludes.

2 Constructing Long-Sample Variance Risk Premiums

In this section, we first define the VRP in Section 2.1. The methodology of extending the implied variance time series is discussed in Section 2.2. We introduce the data in Section 2.3. In Section 2.4, we estimate the long-sample implied variance of individual markets. We discuss the newly constructed VRPs in Section 2.5.

[3] Bollerslev, Marrone, Xu, and Zhou (2014) and Londono (2015) focus on 8 developed markets: the U.S., France, Germany, Japan, Switzerland, the Netherlands, Belgium, and the U.K.. Additionally, the VRP can predict other asset risk premiums, such as currency returns by Londono and Zhou (2017), credit default spreads by Wang, Zhou, and Zhou (2013), and bond risk premiums by Mueller, Vedolin, and Zhou (2011) and Grishchenko, Song, and Zhou (2017).

2.1 Variance Risk Premium Definition

We define the VRP as the difference between expected variance under the risk-neutral measure and expected variance under the physical measure. That is, for market i at month t,

$$VRP_t^i = IV_t^i - E_t(RV_{t+1}^i), \tag{1}$$

where IV_t^i is the expected variance of the market portfolio under the risk-neutral measure or the implied variance, and $E_t(RV_{t+1}^i)$ is the expected variance under the physical measure. For instance, a popular choice for the U.S. implied variance is the squared CBOE's VIX computed from market index option prices. Following the previous literature, such as Andersen and Bollerslev (1998) and Andersen, Bollerslev, Diebold, and Labys (2003), the realized variance is generally annualized and computed by summing daily squared index returns over n trading days within month t. That is,

$$RV_t^i = \frac{252}{n} \sum_{d \in t} r_d^2, \tag{2}$$

where r_d denotes the daily return for day d with all days within month t. Variable $E_t(RV_{t+1}^i)$ is the expectation of RV_{t+1}^i on a set of predictors capturing financial and economic conditions in month t.

We first construct the country-level VRPs. To aggregate the country-level VRPs, we define the global VRP as the value weighted average of country-level VRPs as follows,

$$VRP_t^{Global} = \sum_{i=1}^{n} (w_t^i VRP_t^i), \tag{3}$$

where the weight, w_t^i, is the stock market capitalization in market i at time t divided by the total market capitalization for all markets at time t. The emerging market and developed market VRPs are defined in a similar fashion. If there are commonalities or common risks in the country-level VRPs, aggregating VRPs over the global, developed market, and emerging market levels would be able to better capture these common components.

2.2 Extending Sample Length with the Lynch and Wachter (2013) Methodology

In order to calculate the VRP, we need to obtain both the implied variance from index option prices and the realized variance from index data. Not surprisingly, index options are normally introduced later than the underlying equity market index. Therefore, the implied variance time series, computed from market index options, are much shorter than the realized variance time series, computed from market index data, which is a big obstacle for computing emerging market VRPs. Luckily, Lynch and Wachter (2013) illustrate how to extend samples of unequal length by using the generalized method of moments (GMM). Under the assumption of the consistency and asymptotic normality of the standard GMM estimator, Lynch and Wachter (2013) extend the sample by estimating the moments for which the long-sample data are available, and the moments for which only the short-sample data are available. Then the moments for which only the short sample is available are "adjusted" using coefficients from a regression of the short-sample moments on the long-sample moments.

Following Lynch and Wachter (2013), suppose T denotes the length of the long sample, and λT denotes the length of the short sample for $0 < \lambda \leq 1$. In our setting, the realized variance and predictive variables are observable in the long sample over $t = 0, ..., T$, while the implied variance is only observable in the short sample over $t = (1-\lambda)T, ..., T$. We start by considering a linear projection of the natural logarithm of realized variance on the space spanned by predictive variables that track the financial and economic conditions,

$$log(RV_{t+1}) = z_t\theta_1 + \varepsilon_{rv,t+1}, \tag{4}$$

where the 1 by J vector z_t includes a constant and $J-1$ predictors at time t, and θ_1 is the J by 1 vector of parameters. A similar projection is also defined for the natural logarithm of implied variance,

$$log(IV_t) = z_t\theta_2 + \varepsilon_{iv,t}. \tag{5}$$

We choose to model the natural logarithm of these two variances instead of the level, because the natural logarithm form is empirically closer to a normal distribution, and it guarantees that the predicted realized variance and implied variance are positive. Notice that equation (4) is a predictive relation, while equation (5) is a contemporaneous relation. This is because realized variance measures the return variation, and the predictive relation in equation (4) provides the physical expectation of the return variation. On the other hand, implied variance is already the risk-neutral expectation of the future return variance. Thus, a predictive relation is unnecessary for implied variance.

Moment conditions for the long-sample natural logarithm of realized variance, and moment conditions for the short-sample natural logarithm of realized variance and implied variance are defined as following,

$$\begin{aligned} g_{1,T}(\theta_1) =& \frac{1}{T}\sum_{t=0}^{T-1} f_1(z_t,\theta_1) = \frac{1}{T}\sum_{t=0}^{T-1}(log(RV_{t+1}) - z_t\theta_1)z_t, \\ g_{1,\lambda T}(\theta_1) =& \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1} f_1(z_t,\theta_1) = \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1}(log(RV_{t+1}) - z_t\theta_1)z_t, \\ g_{2,\lambda T}(\theta_2) =& \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1} f_2(z_t,\theta_2) = \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1}(log(IV_t) - z_t\theta_2)z_t. \end{aligned} \tag{6}$$

From estimating the long-sample and short-sample time-series regression of $log(RV_{t+1})$ on predictors z_t in equation (4), we obtain $\hat{\theta}_{1,T}$ and $\hat{\theta}_{1,\lambda T}$. From estimating the short-sample time-series regression of $log(IV_t)$ on predictors z_t in equation (5), we obtain $\hat{\theta}_{2,\lambda T}$. To construct the long-sample estimator $\hat{\theta}_{2,T}$, we need a $J * J$ adjustment matrix $\hat{B}_{21,\lambda T}$. The long-sample estimator $\hat{\theta}_{2,T}$ is estimated by setting the long-sample moment conditions $g_{2,T}(\theta_2)$ to zero,

$$g_{2,T}(\theta_2) = g_{2,\lambda T}(\theta_2) + \hat{B}_{21,\lambda T}(g_{1,T}(\theta_1) - g_{1,\lambda T}(\theta_1)). \tag{7}$$

We use $\hat{\theta}_1 = \hat{\theta}_{1,T}$ and $\hat{\theta}_2 = \hat{\theta}_{2,T}$ as the final estimated coefficients for constructing the expected realized variance and expected implied variance. Other estimation details and the distribution of these estimated coefficients $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2]$ are discussed in Appendix A.

2.3 Data

Our sample period is from January 2000 to October 2017, for a total of 214 months. We include data from 9 emerging markets, and they are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan.[4] We do not include other emerging markets in the paper mainly because their index option data are not available. To benchmark our study to related studies in international finance, we also collect data from 11 developed markets: Australia, Belgium, Canada, France, Germany, Hong Kong (HK), Japan, the Netherlands, Switzerland, the U.K., and the U.S..

We plot annual GDP and monthly market capitalizations for developed markets, emerging markets, the U.S., and China in Figure 1. Panel A shows the annual current price GDP in trillion dollars. The total GDP of our 9 emerging markets was 4.5 trillion dollars, accounting for 16.8% of the global GDP in 2000. In 2017, the emerging market GDP rose to 21.8 billion dollars and accounted for 36.6% of the global GDP. In terms of global capital markets, emerging markets enjoy a rapid growth and have become an important part of the global capital markets as shown in Panel B. For instance, in 2000, the total equity market capitalization of our sample 9 emerging markets was 1.3 trillion dollars, accounting for less than 5% of the global equity market. As of October 2017, this number jumped to 11.2 trillion dollars, accounting for more than 18% of the global equity market. In terms of developed markets, its market share decreased from 95.12% in 2000 to 81.5% in 2017. Take two markets as examples, the U.S. accounted for 49.43% of the global equity market in January 2000. However, the subprime crisis in 2007 and 2008 put a big dent in the U.S. equity market, and in 2017, the U.S. accounted for 36.17% of the global market capitalization. Over the same time period, China quickly climbed up in the market capitalization, accounting for about 0.3% of the global equity market in 2000, and 8.27% in 2017.

[Insert Figure 1 Here]

For each market, we obtain data on implied volatility and realized variance from stock market indices. Table 1 Panel A provides the name and the starting date for the model-free implied volatility, the corresponding underlying equity index, and the data source for the implied volatility. Out of 9 emerging markets, three equity indices started before 1990, and

[4] According to Statistic Times in 2017, China, India, Brazil, Korea, Russia, and Mexico rank in top 6 for GDP contribution in emerging markets with a descending order. Taiwan, Poland, and South Africa are ranked in the 11th, 12th, and 16th places among emerging markets, respectively.

the other six started between 1990 and 2000.[5] All of the model-free implied volatility indices in emerging markets started after January 2000, with Korea VKOSPI (volatility index for KOSP 200) as the earliest in January 2003, and China IVX (volatility index for SSE 50) as the latest in February 2015. Interestingly, different markets adopt different methodologies to compute implied market volatilities, relying on options with different moneyness or different maturities. For instance, Brazil, China, India, Korea, Mexico, Russia, and Taiwan follow a similar approach to CBOE's VIX construction, and the implied volatility is estimated by averaging the weighted prices of near maturity index puts and calls over a wide range of strike prices. More details are provided in Appendix B. Even though various markets adopt different methodologies for computing market volatility indices, all of them reflect implied volatility from option data. From Panel A, it is clear that the implied variance time series are much shorter than the market index time series. To conduct a comprehensive study on emerging market VRPs, without excluding the largest emerging market, China, one might need to start from 2015 based on data availability.

[Insert Table 1 Here]

We report similar data items for developed markets in Table 1 Panel B. Most of the equity indices started in the 1980s or even 1960s, and the model-free implied volatility started before January 2001 except for Australia, which started in 2008, and Canada, which started in 2002. Clearly, the equity indices and the model-free implied volatility from developed markets have much longer sample periods than those from emerging markets.

Table 2 reports summary statistics on all stock market returns. Over our sample period, the annualized monthly returns of many emerging market stock indices, such as India Nifty 50, Mexico IPC, Russia RTS, and South Africa JSE Top 40, are all well above 12% on average. In contrast, the average annualized monthly returns of all developed markets are below 6%. In terms of the corresponding standard deviations, developed stock markets are less volatile than emerging stock markets. The most volatile developed stock market is Germany DAX

[5] The China SSE 50 index began in January 2004. We construct the index from 1997 to 2003 following the procedure to select the 50 largest and most liquid firms traded in the Shanghai Stock Exchange.

and HK Hengsheng, with an annualized standard deviation of 21%. However, 7 out of 9 emerging markets have standard deviations well above 21%. While the evidence of a large negative skewness is common in developed stock markets, the skewness in emerging markets is much smaller and even positive for China SSE 50, Poland Wig 20, and Taiwan TAIEX, which is consistent with the previous studies, such as Ghysel, Plazzi, and Valkanov (2016). All returns are fat tailed with high kurtosis.

[Insert Table 2 Here]

Turning to Panel B of the table, the correlations of stock market returns in emerging equity markets are all below 0.67. In particular, the correlations of China SSE 50 and all other markets are well below 0.33, with one exception, its correlation with HK Hengsheng is 0.48. Similarly, the correlations of emerging stock markets and developed stock markets are also low, ranging from 0.23 to 0.7. In comparison, the correlations of returns in developed stock markets are quite high, ranging from a low of 0.61 to a high of 0.92. The only exception is correlations with Japan Nikkei 225 and HK Hengsheng, and the correlations are mostly between 0.52 and 0.69. Clearly, stock returns in emerging markets are very different from those in developed markets. Lower correlations normally indicate higher diversification benefit. As a result, emerging markets provide better diversification opportunities than developed markets for investors.

2.4 Implied Variance Extension

To extend implied variance and to estimate the ex-ante expectation of realized variance, we need a set of macroeconomic variables z_t, that can predict/describe the time series of variances.

It is well known that variance processes are persistent and asymmetric with respect to positive and negative return shocks (see Engle and Ng, 1993). Following Bekaert and Hoerova (2014), we include the lagged natural logarithm of realized variance, $log(RV_t)$, the downside monthly return, $Return21$, the downside weekly return, $Return5$, and the downside daily return, $Return1$, to account for persistence and asymmetry.

According to Bollerslev, Gibson, and Zhou (2011) and Campbell, Giglio, Polk, and Turley (2015), the inflation rate can affect the dynamics of VRPs and aggregate wealth. So we include the inflation rate, computed as the natural logarithm difference of the consumer price index CPI. Paye (2012) states that the real GDP growth rate has predictive ability on aggregate market volatility. So we compute the real GDP growth rate as the natural logarithm difference of real GDP (Gross Domestic Product by expenditure in constant prices).[6] In addition, we also include the unemployment rate, the M1 growth rate, and the economic policy uncertainty index. In market downturn, the government usually adopts a loose monetary policy (increasing M1) to stimulate the economy. Therefore, we include the M1 growth rate. Boutchkova, Doshi, Durnev, and Molchanov (2012) show that local political risk is related to systemic volatility. So we include the Economic Policy Uncertainty index, provided by the website http://www.policyuncertainty.com/, as in Baker, Bloom, and Davis (2016).[7]

In Table 1 Panel C, we summarize the availability and frequency of these macroeconomic variables, which are mainly collected from the Fed Reserve website and Bloomberg. For a quarterly macroeconomic variable, we forward fill the months within the quarter. Unfortunately, we are unable to include all important predictive macroeconomic variables documented in the previous literature, due to data availability. Note that if a macroeconomic variable starts later than January 2000, it would be excluded from our estimation steps. We use the Lynch and Wachter (2013) approach described in Section 2.2 to extend implied variance in 9 emerging markets, from January 2000 to October 2017. We choose to extend the sample to 2000 to match the time series of realized variance, which are available for all markets after 2000.

Table 3 presents the results for the unequal length sample estimation. For each emerging

[6] We do not include price-to-earnings ratios, because its dynamics are mostly driven by the price, and it is highly correlated to the real GDP growth rate in general.

[7] Barras and Malkhozov (2016) employ a set of five macro-finance predictors to capture volatility and economic conditions: the lagged realized variance, the price-to-earnings ratio, the quarterly inflation rate, the quarterly growth in aggregate employment, and the default spread. The theoretical motivation for using these variables as well as their ability to predict realized variance are discussed in the recent studies of Bollerslev, Gibson, and Zhou (2011), Paye (2012), and Campbell, Giglio, Polk, and Turley (2015).

market, we report four sets of estimation results: short-sample projections of $log(RV_{t+1})$ and $log(IV_t)(t = (1-\lambda)T, ..., T-1)$, and long-sample projections of $log(RV_{t+1})$ and $log(IV_t)(t = 0, ..., T-1)$. Since the estimators are exactly identified, and the instrumental variables are the same as the predictor variables, the GMM estimators for the short sample, $\theta_{1,\lambda T}$ and $\theta_{2,\lambda T}$, and the long sample, $\theta_{1,T}$, are exactly the same as those from OLS regressions. Notice that the long-sample estimator, $\theta_{2,T}$, may not be the same as the short-sample estimator, $\theta_{2,\lambda T}$, because the short sample may not be representative of the long sample. In this case, we follow Lynch and Wachter (2013) and adjust the estimators to improve the estimation precision, using the relation between $log(RV_{t+1})$ and z_t in the long sample, and the relation between $log(RV_{t+1})$ and $log(IV_t)$ in the short sample.

[Insert Table 3 Here]

In the short sample, we find that all 9 $log(RV_{t+1})$ are well fitted by the predictor variables z_t with the adjusted R^2 ranging between 39% (Brazil) and 75% (China). Similarly, the dynamics of $log(IV_t)$ are also well specified by the predictor variables z_t for all emerging markets in the short sample period. The adjusted R^2 is remarkably high for China, being 90%. The adjusted R^2s become lower in the long sample, indicating that the earlier sample is hard to be fitted equally well as in the latter sample based on the same model specification. Still, they range from 43% to 66%. There is no adjusted R^2 measure for the last regression of long-sample $log(IV_t)$, because the coefficients are fitted using a transformation of coefficients in the previous three regressions.

We report the estimated coefficients and t-statistics, adjusted for White (1980) standard errors for each of the predictive variables z_t.[8] The lagged realized variance $log(RV_t)$ has a significant and positive effect on both $log(RV_{t+1})$ and $log(IV_t)$ in all emerging markets, because of the persistence in volatility measures. Downside returns $Return1$, $Return5$, and $Return21$ have negative coefficients in general, indicating that a shock in downside returns is expected to lead to an increase in the future volatility on average, which captures the

[8] Lynch and Wachter (2013) assume that the errors are uncorrelated. We follow the procedure by Stambaugh (1997) and Lynch and Wachter (2013) to apply White (1980) standard errors to adjust the estimators.

asymmetry in the variance measures. Among the macroeconomic variables, the inflation rate has a significant positive effect on India and Taiwan $log(IV_t)$, while the other markets inflation rates have no significant effects at the 5% level. The real GDP growth rate represents the overall economic condition—a decrease in the real GDP growth rate indicating deterioration in the investment opportunities, which may lead to an increase in stock market uncertainty. That is exactly what we find for China, Mexico, and Taiwan. The M1 growth rate has different effects on $log(RV_{t+1})$ and $log(IV_t)$ in different markets. The evidence of the unemployment rate effect is also mixed. Finally, the economic policy uncertainty index has a significant negative effect on $log(RV_{t+1})$ in China and Korea.[9]

2.5 Extended Variance Risk Premiums

With the extended implied variance, the extended VRP is computed as follows:

$$\begin{aligned} VRP_t =& IV_t - E_t(RV_{t+1}) \\ =& \begin{cases} e^{z_t\theta_{2,T}+\frac{1}{2}\sigma^2_{\varepsilon,iv}} - e^{z_t\theta_{1,T}+\frac{1}{2}\sigma^2_{\varepsilon,rv}}, & \text{for } t = 1, ..., (1-\lambda)T, \\ IV_t - e^{z_t\theta_{1,T}+\frac{1}{2}\sigma^2_{\varepsilon,rv}}, & \text{for } t = (1-\lambda)T+1, ..., T, \end{cases} \end{aligned} \tag{8}$$

where IV is the model-free implied variance, and RV is the realized variance. The extended IV is $e^{z_t\theta_{2,T}+\frac{1}{2}\sigma^2_{\varepsilon,iv}}$. The expectation of RV_{t+1} at the end of month t, $E_t(RV_{t+1})$, is equal to $e^{z_t\theta_{1,T}+\frac{1}{2}\sigma^2_{\varepsilon,rv}}$. Variables $\sigma^2_{\varepsilon,rv}$ and $\sigma^2_{\varepsilon,iv}$ are the variances of the residuals from equation (4) and equation (5), respectively.

Figure 2 shows the time-series plots of these uncertainty measures—monthly realized variance, implied variance, and VRPs for each market.[10] The time series of various variance measures appear to capture major economic events. During the internet bubble period 2000-2002, there was some obvious turbulence in both implied variance and realized variance of all 9 emerging markets. During the 2008 global financial crisis, all the uncertainty measures

[9] In Appendix C, we conduct an out-of-sample test for the sample extension method, in which we apply the method to the second half of the observed implied variance data by pretending that the first half of the observed sample data is missing. We then examine whether the sample extension method can generate reasonable time series for the first half of the sample, and compare with the real observed data from the first half sample period. We find that the correlation of the time series from the sample extension method and from real data is on average 79%, which shows that the sample extension method provides a reasonable good fit out of sample.

[10] The plots of the fitted implied variance and realized variance in the short and long samples for each market are shown in Appendix D.

in all emerging markets became exceptionally large. For instance, Russia had the spike in implied variance at 2500 squared percent, mostly because oil price plummeted at the same time as the global financial crisis, while Russia is an oil exporter. During the 2011 European sovereign debt crisis, many emerging markets, except for China and India, were largely adversely influenced, showing common peaks in these uncertainty measures. There are also some country-specific events leading to the changes in these uncertainty measures, but with little spill-over effect on other markets. For example, in June 2015, China experienced substantial spikes in both implied variance and realized variance. However, there were no obvious changes in either implied variance or realized variance for all other emerging markets around the same time.

[Insert Figure 2 Here]

Table 4 reports summary statistics on implied variance, realized variance, and VRPs in monthly percentage squared unit for both 9 emerging markets and 11 developed markets from January 2000 to October 2017. In Panel A, compared to the U.S., the emerging market implied variance and realized variance are larger on average. For instance, the U.S. implied variance is on average 38.67, while the emerging market implied variance ranges between 42.02 (Mexico) and 128.07 (Russia). The U.S. realized variance is 29.42, while the emerging market realized variance ranges between 33.97 (Mexico) and 120.38 (Brazil). This pattern indicates that emerging markets may have much higher economic uncertainty on average. Both implied variance and realized variance have large variations, with positive skewness and large kurtosis. The fact that implied variance is on average higher than realized variance in almost all markets directly leads to mostly positive VRPs, ranging from a low value of -5.58 (Brazil) to a high value of 34.67 (Russia). For developed markets, we find that the averages of all country-level VRPs are positive. Japan has the largest mean value of 15.01, while Canada has the smallest mean value of 5.01. The average U.S. VRP is 9.06.

[Insert Table 4 Here]

We compute the emerging market VRP, the developed market VRP, and the global VRP, and present their summary statistics in the last three rows. The time-series means are 7.08, 9.53, and 9.38 for the emerging market, developed market, and global VRPs, respectively. The emerging market VRP is much more volatile than the developed market and global VRPs, with a larger positive skewness and a much fatter tail. The AR(1) coefficients for both the global and developed market VRPs are 0.36. They are smaller than the emerging market VRP AR(1) coefficient at 0.46, indicating that the emerging market VRP is more persistent than the developed market VRP.

Panel B of Table 4 reports the correlations among global, emerging market, developed market VRPs, and country-level VRPs in 9 emerging markets and 11 developed markets. Putting China and Brazil aside, the VRPs in emerging markets are largely and positively correlated, ranging from a low correlation value of 0.30 (Mexico and Taiwan, Russia and Taiwan) to a high correlation value of 0.71 (Poland and Mexico). But these seven markets' VRPs are not correlated much with China and Brazil VRPs. For developed markets, putting Japan aside, all correlations are positive.[11] The smallest correlation is 0.01 (Switzerland and Belgium), and the largest correlation is 0.90 (the U.K. and the Netherlands). The correlations among developed markets are generally higher than those among emerging markets. At the bottom of the table, the correlation between the developed market VRP and the global VRP is 97%, implying that the two probably contain similar information. However, the correlation between the emerging market VRP and the developed market VRP is merely 31%, indicating that the VRPs from emerging markets and developed markets are substantially different. The correlation between the emerging market VRP and the global VRP is 51%.

Figure 3 presents the time-series plots of these three VRP variables over January 2000 to October 2017. Interestingly, the dynamics of emerging market and developed market VRPs are distinctively different. The biggest spike for the emerging market VRP was around the 2008 global financial crisis, and the emerging market VRP was highly positive at close to 200 squared percent. The biggest spike for the developed market VRP also happened around 2008, yet the developed market VRP was largely negative at -120 squared percent. There were other smaller spikes in both time series, and we can detect the 2015 China market turbulence in the emerging market VRP, and the 2002 internet bubble and 2011 European

[11] We also compute VRPs from different geographic regions, and the results are discussed in Section 4.3.2.

sovereign debt crisis in the developed market VRP. For the global VRP in Panel C, due to the large weights on developed markets, it is more similar to the developed market VRP than the emerging market VRP.

[Insert Figure 3 Here]

3 Predicting Stock Market Returns, Currency Returns, and Capital Flows

The previous literature, such as Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), Bollerslev, Marrone, Xu, and Zhou (2014), Londono (2015), and Londono and Zhou (2017) shows that for the U.S. and other developed markets, the VRP is a powerful predictor for stock market returns and currency returns, potentially because the VRP captures aggregate economic uncertainty. In this section, we investigate whether the VRPs constructed from emerging markets are also systematic state variables relevant for future financial market conditions.

In Section 3.1, we use VRPs from individual markets, emerging markets, developed markets, and global markets to predict stock market returns. We examine the predictive power of various VRPs for currency returns and capital inflows in Sections 3.2 and 3.3, respectively.

3.1 Stock Market Return Predictability

Bollerslev, Marrone, Xu, and Zhou (2014) use the global VRP to predict developed market stock index returns in panel regressions. With the same specification, we examine the predictive power of the country-level VRP (VRP^i), the emerging market VRP (VRP^{EM}), the developed market VRP (VRP^{DM}), and the global market VRP (VRP^{Global}) for stock market index returns. The panel regression with the country fixed effect is specified as follows,

$$r^i_{t+1,t+h} = a_h + b_h VRP_t + CountryFE^i + \epsilon^i_{t+1,t+h}, \tag{9}$$

where $r^i_{t+1,t+h}$ denotes the cumulative stock returns over month $t+1$ to month $t+h$ for market i, VRP_t can be one of or combinations of VRP^i, VRP^{EM}, VRP^{DM}, and VRP^{Global}

in month t, and $h = 1, ..., 24$ months. The standard errors are estimated using the Newey and West (1987) method with h lags to account for autocorrelation in the error terms. In this setup, we can examine the significance of VRPs by testing whether b_h is significantly different from zero. We can also investigate the different information contents of the various VRP variables.

We first examine the stock market return predictability in local currency in 9 emerging markets: Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. The estimation results from the panel regressions in equation (9) are reported in Table 5.[12] Panel A shows the results based on the country-level VRP. We find that all coefficients on VRP^i are positive, and for horizons longer than 5 months, the coefficients are all statistically significant at the 5% level. In terms of magnitude, for $h = 6$, a $1\%^2$ increase in monthly VRP^i leads to 0.09% increase in annualized stock returns over next 6 months. The finding that VRP^i can significantly predict own country's future stock market returns in emerging markets is new and consistent with the findings in previous studies on developed markets. However, the explanatory power of VRP^i is generally low, with the R^2s ranging between 0.0% and 1.7%.

[Insert Table 5 Here]

In Panel B, we examine the predictive power of the emerging market VRP. If there is the common risk component in emerging market country-level VRPs, VRP^{EM} might be able to significantly predict future stock market returns. If the common component of the country-level VRPs contains more information about future financial conditions than country-level VRPs, we might find the R^2s using VRP^{EM} to be higher than using single market country-level VRPs. Interestingly, all coefficients on VRP^{EM} over all predicting horizons are significantly positive at the 1% significance level. For instance, for the 1-month horizon, a $1\%^2$ increase in monthly VRP^{EM} would lead to 0.39% increase in annualized stock returns over the next 1 month. The R^2s using VRP^{EM} range from 1.1% to 7.5%,

[12] Our result remains when using stock market returns in U.S. dollars for each market. The result is not reported.

peaking at months 8 and 10. The higher significance and R^2 of VRP^{EM} over country-level VRPs indicate that the common component of the emerging market VRPs contains more information than country-level VRPs for future stock market returns.

In Panel C, we investigate whether the common component of VRPs from individual developed market country-level VRPs can predict future market returns in emerging markets. If the VRP is a global risk factor, and given VRP^{DM} is highly correlated with VRP^{Global}, we expect that VRP^{DM} can predict future emerging market country-level stock returns. For $h = 1$ to 8, we find that the coefficients on VRP^{DM} are all positive and highly significant, with the R^2s ranging between 1.0% and 5.0%. For $h = 9$ to 24, however, the predictive power of VRP^{DM} diminishes and becomes insignificant. This finding is consistent with the finding in Bollerslev, Marrone, Xu, and Zhou (2014) that the predictive power of the developed market VRP is strong over short horizons.

In Panel D, we directly use the global common component of VRPs from both emerging markets and developed markets for predicting future stock market returns in emerging markets. Given that VRP^{Global} contains information from both VRP^{DM} and VRP^{EM}, with VRP^{DM} being significant over shorter horizons $h = 1$ to 8, and VRP^{EM} over all horizons, maybe it is not that surprising that VRP^{Global} is significant for all horizons except around $h = 18$. Given that VRP^{Global} is 97% correlated with VRP^{DM}, the pattern of R^2s resembles those in Panel C, and the magnitudes of R^2s are smaller than those in Panel B with VRP^{EM} over longer horizons for $h > 5$. The significance of VRP^{Global} shows that the predictive information in VRPs is systematic and affects all emerging markets.

Given that the correlation between VRP^{EM} and VRP^{DM} is only 31%, it is intriguing to understand which of the two has stronger predictive power for future stock market returns. In other words, it is important to differentiate the information content between VRP^{EM} and VRP^{DM}. Therefore, in Panel E of Table 5, we include both for predicting emerging stock market returns. On one hand, the inclusion of VRP^{DM} weakens the statistical significance of VRP^{EM} for shorter horizons from 1 to 3 months, but VRP^{EM} stays positive and significant for all longer horizons. On the other hand, the inclusion of VRP^{EM} weakens the statistical significance of VRP^{DM} mainly for longer horizons, and for $h = 7$ to 12, the coefficients on VRP^{DM} even become negative yet insignificant. In terms of the R^2, the inclusion of both variables clearly increases the overall explanatory power. The R^2s become higher than those in all other panels, including those in Panel D with VRP^{Global}, which is a weighted average of VRP^{EM} and VRP^{DM}, implying that free parameters on these two components bring on higher explanatory power. Overall, the predictive power of VRP^{DM} and VRP^{EM} is distinctive and complementary, with VRP^{DM} mostly significant over shorter horizons up to 3 months, and VRP^{EM} mostly significant over longer horizons.[13]

Do the above patterns hold in developed markets or all markets? Next, we expand the testing sample to 11 developed markets and 9 emerging markets, and the results are reported in Table 6. Notice that with more developed markets than emerging markets, the results could be more influenced by developed markets.

[Insert Table 6 Here]

In Panel A, we start with country-level VRPs to predict its own future stock market returns. The coefficients on VRP^i are all positive, and are significant for horizons longer than 4 months, indicating that local information contained in VRPs is important for future market conditions. In Panel B, we use VRP^{EM} to predict country-level stock market returns. Surprisingly, even with 11 additional developed markets, the common component in emerging market country-level VRPs has positive and significant predictive power for country-level stock market returns over all horizons, especially for h larger than 3 months. The R^2s range from 0.9% to 7.6%, peaking at month 10. For comparison, we only include VRP^{DM} in Panel C. Slightly different from VRP^{EM}, which is significant for all horizons, the coefficients on VRP^{DM} are also significant over all horizons, except when $h = 18$, and the significance is more prominent over short horizons. The R^2s range between 0.1% and 4.9%, smaller than

[13] We also conduct additional estimation examining whether country-specific VRPs are still relevant in the presence of common components in VRPs. That is, we estimate country-specific VRPs by regressing country-level VRPs on VRP^{EM}, VRP^{DM}, and VRP^{Global}, and the residual part is orthogonal to the common component, and is country-specific VRPs. We report these results in Appendix E Table E1. We find that country-specific VRPs are insignificant, and carry negative signs in the presence of VRP^{EM}. As we already know that information contents of VRP^{DM} and VRP^{Global} are different from VRP^{EM}. So in the presence of either VRP^{DM} or VRP^{Global}, country-specific VRPs can still be significant, and have positive signs over longer horizons.

those of VRP^{EM} over longer horizons. We include only VRP^{Global} in Panel D. Given the high correlation between VRP^{DM} and VRP^{Global}, the results are quite similar to those in Panel C. Finally, both VRP^{EM} and VRP^{DM} are put together in Panel E. The results confirm these in Panel E of Table 5, even though we include 11 additional developed markets. The slope coefficients on VRP^{EM} are always significant and positive over all horizons, indicating its importance as a common risk indicator for all markets, more so for horizons longer than 3 months. Variable VRP^{DM} is also very important, especially over horizons up to 7 months, for which it is always positive and statistically significant. For horizons longer than 7 months, however, the explanatory power of VRP^{DM} is dominated by VRP^{EM}, and the coefficients become insignificant or negative.

For robustness, we also examine the predictive power of VRPs for all MSCI markets, with 23 emerging markets and 23 developed markets. The results are discussed in Section 4.3.1, and they are quite similar to those in Table 6.

Overall, both Tables 5 and 6 confirm the existing empirical evidence that a higher (lower) VRP tends to be associated with higher (lower) returns over the next 1 to 24 months. The common component of country-level VRPs in the global capital markets is quite important for future stock return predictions in emerging markets. The developed market VRP is more important over shorter horizons, while the emerging market VRP is more important over longer horizons, indicating that they contain differential and complementary information over different horizons.

What explains the different predictive patterns of VRP^{DM} and VRP^{EM} over different horizons? According to Bollerslev and Zhou (2008), the VRP can be driven by two volatility factors—cash flow volatility and discount rate volatility, as follows,

$$\begin{aligned} VRP =& E_t^Q(Var_{t+1}) - E_t^P(Var_{t+1}), \\ \approx& Cov_t[m_{t+1}, Var_{t+1}(r)], \\ =& A * \sigma_{g,t}^2 + B * q_t, \end{aligned} \tag{10}$$

with $A > 0$ and $B > 0$. Variable m_{t+1} is the stochastic discounting factor, $\sigma_{g,t}^2$ is the cash flow volatility or consumption growth volatility, and q_t is the volatility-of-volatility or discount rate volatility. As discussed in Bollerslev, Xu, and Zhou (2015), the persistence levels of the volatility-of-volatility and the cash flow volatility are different—0.46 versus 0.64. We may call the volatility-of-volatility as "discount rate volatility", because it is orthogonal with the cash flow volatility (Bansal, Kiku, Shaliastovich, and Yaron, 2014). That is, the discount rate volatility is less persistent than the cash follow volatility, and the discount rate volatility would predict returns over shorter horizons, while the cash flow volatility would predict returns over longer horizons.

In our case, it is possible that VRP^{EM} loads more on the cash flow volatility, which is more long-term, while VRP^{DM} loads more on the discount rate volatility, which is more short-term. Consequently, VRP^{EM} would predict returns in longer horizons, while VRP^{DM} would predict returns in shorter horizons. We find supportive evidence for above hypothesis in the data.

First, Table 4 shows that VRP^{EM} has an AR(1) coefficient of 0.46, while VRP^{DM} has an AR(1) coefficient of 0.36, which shows that the former is a bit more persistent than the latter. Next, we compute a proxy for discount rate volatility using the three-month U.S. treasury bill rate volatility over past 3 years, and a proxy for cash flow volatility using the GDP growth rate volatility over past 3 years. The correlation between the discount rate volatility proxy and VRP^{DM} is 0.24 and highly significant, while the correlation with VRP^{EM} is 0.09 and statistically insignificant. This finding implies that VRP^{DM} captures more information regarding the discount rate volatility. The correlation between the global GDP growth volatility and VRP^{DM} is 0.18 and insignificant, and the correlation with VRP^{EM} is 0.11 and insignificant. However, the driver of global economic growth and especially its volatility is emerging markets. The correlation between the emerging market GDP growth volatility and VRP^{DM} is 0.21 and insignificant, and the correlation with VRP^{EM} is 0.33 and highly significant. This finding suggests that the latter is much highly correlated with the GDP growth in emerging markets. Notice that most of the global GDP growth is driven by emerging markets, it is likely that between VRP^{DM} and VRP^{EM}, the latter represents more of the cash flow volatility. Therefore, our suggestive explanation is that VRP^{DM} is less persistent and more related to the discount rate volatility, and its predictive power is mostly over shorter horizons, while VRP^{EM} is more persistent and more related to the cash flow volatility, and its predictive power dominates over longer horizons.

3.2 Foreign Currency Return Predictability

The currency forward premium puzzle has been long standing since Fama (1984). Because of pervasive violations in the uncovered interest parity, interest rate differentials cannot predict exchange rate returns. Thus, forecasting exchange rates has been a difficult issue for finance practitioners and academics for decades (see Meese and Rogoff, 1983, among many others). In this section, we use VRPs to predict currency returns following Londono and Zhou (2017).

We obtain exchange rate data from Bloomberg. The exchange rates (FX) are quoted in units of U.S. dollar per one unit of foreign currency, and a positive sign corresponds to an appreciation of the foreign currency with respect to the U.S. dollar. The currency returns at time t are defined as $\frac{FX_t - FX_{t-1}}{FX_{t-1}}$. Notice that the currency rate is determined by economic conditions of the home country and the U.S..[14]

We estimate the predictive power of VRPs for currency returns with the following specification,

$$r^i_{t+1,t+h} = a_h + b_h VRP_t + c_h r^i_{LM,t} + d_h r_{US,t} + CountryFE^i + \epsilon^i_{t+1,t+h}, \tag{11}$$

where $r^i_{t+1,t+h}$ denotes the cumulative currency returns over month VRP_t represents one of or combinations of VRP^i, VRP^{EM}, VRP^{DM}, and VRP^{Global} in month t, variables $r^i_{LM,t}$ and $r_{US,t}$ denote the local stock market returns and U.S. stock market returns in month t for market i, respectively, and $h = 1, 2, ..., 24$ months. We also control for the country fixed effect.

Table 7 provides the results. In Panel A, after we control for local and U.S. market returns, we find that VRP^i has no predicting power for currency returns over all horizons.[15]

[14]Authorities in many markets implement regulations over currency rates. For instance, China's exchange rate is managed floating, which is not free floating but still reflects market conditions. Before 2005, China pegged exchange rate with the U.S. dollar as anchor. After 2005, it changed to the crawl-like arrangement floating rate (monetary aggregate target), and then became the managed floating rate after December 2014. The managed floating rate regime includes Brazil, India, Korea, South Africa, and Taiwan. The free-floating regime includes Poland, Mexico, and Russia (Russia was the managed floating regime before 2015.).

[15]From unreported results, the country-level VRP can positively and significantly predict future currency returns by itself. Combined with the coefficients on the market index returns, this finding indicates that the predictive power of country-level VRPs roots from its predictive power for local market index returns.

Since the currency rate is the ratio between local currency value and U.S. dollar value, it is not surprising to find that local stock market returns consistently and positively predict currency returns, while U.S. stock market returns negatively predict currency returns.

[Insert Table 7 Here]

In Panel B, we use VRP^{Global} instead of VRP^{i}. Even though local and U.S. market returns are still significant with expected signs, VRP^{Global} itself has positive predictive power for currency returns, and the coefficients of which are all significant at 1% level over all horizons considered. For instance, at the 1-month horizon, a $1\%^2$ increase in monthly VRP^{Global} would lead to 0.42% increase in annualized currency returns over the next 1 month. The R^2 in these regressions has the maximum value of 6.7% at the 5-month horizon, and gradually tapers off as the horizon grows. This finding indicates that VRP^{Global} contains more systematic risk that is not captured in local and U.S. stock market returns.

We include both VRP^{DM} and VRP^{EM} in Panel C. With the control of local and U.S. stock market returns, the coefficients on VRP^{EM} remain significantly positive over longer horizons after 6 months, while the coefficients on VRP^{DM} are more significant over shorter horizons. In addition, the R^2s are even higher than those in Panel B. This predictive pattern of VRP^{EM} and VRP^{DM} for currency returns mirrors their predictive pattern for stock market returns in Section 3.1.

Our results that VRP^{Global} and VRP^{DM} have strong positive predictive power for foreign currency returns with respect to the U.S. dollar at the short horizon are consistent with the findings of Londono and Zhou (2017), who find that the U.S. stock VRPs have positive, nonredundant, and significant predictive power for the appreciation rates of 22 currencies with respect to the U.S. dollar, especially at 1- to 4-month horizons. The stock VRP is interpreted as a function of the country's domestic real growth uncertainty, and in particular, a function of the country's uncertainty of real consumption growth volatility, which is the dominate source of variation in the equity premium. Our novel finding additionally shows that the emerging market VRP is also important for currency return predictions, and its predictive power dominates over longer horizons. The results expanded to all MSCI countries are similar, and are discussed in Section 4.3.1.

3.3 Net Capital Inflow Predictability

As documented in Broner, Didier, Erce, and Schmukler (2010), international capital flows among emerging economies increased dramatically in the past decades, because of the increasing role of emerging markets in globalization. This upward trend, however, has been interrupted during the global financial crisis period in 2008. According to Forbes and Warnock (2012), international capital flows have undergone a series of cycles or "waves" over the last decade, which makes it difficult to predict capital flows. There has been rapidly growing literature on predicting capital flows with economic uncertainty measures. For example, Gourio, Siemer, and Verdelhan (2016) find that when a country's stock market volatility increases, net capital inflows decrease, which is driven by a large decline of capital inflows (by foreigners) with partial offset by a decline of capital outflows (by residents). However, their study only focuses on stock market volatility and its capital flow predictability in the next one quarter. In this section, we investigate whether VRPs provide direct and non-redundant predictive power for capital inflows over longer horizons.

To measure capital flows, we use gross international capital flows compiled by Bluedorn, Duttagupta, Guajardo, and Topalova (2013) from the IMF balances of payments (version 5), supplemented with other IMF and country sources. Gross outflows are defined as net purchases of foreign financial instruments by domestic residents. Gross inflows are defined as net sales of domestic financial instruments to foreign residents. Net capital inflows are defined as the difference between gross outflows and gross inflows. Capital flows are measured at the quarterly frequency, and all series are scaled by country-level GDP, and are seasonally adjusted using the X-12-Arima seasonal adjustment procedure.

Clearly, capital flows in and out of a country are affected by the country's economic conditions and its currency value. After controlling for stock market index returns and currency returns, we examine whether VRPs help predict future capital flows as follows,

$$CF^i_{t+1,t+h} = a_h + b_h VRP_t + c_h r^i_{LM,t} + d_h r^i_{FX,t} + CountryFE^i + \epsilon^i_{t+1,t+h}, \qquad (12)$$

where $CF^i_{t+1,t+h}$ denotes the cumulative net capital inflows from quarter $t+1$ to quarter $t+h$ for market i, variable VRP_t represents one of or combination of VRP^i, VRP^{EM}, VRP^{DM}, and VRP^{Global} in quarter t, variables $r^i_{LM,t}$ and $r^i_{FX,t}$ denote local stock market returns and currency returns in quarter t for market i, respectively, and $h = 1, 2, ..., 8$ quarters. The predictive regressions for capital inflows are different from the earlier predictive regressions in two aspects. First, the sample period is from 2000 to 2012, which is the most updated and complete data from Bluedorn, Duttagupta, Guajardo, and Topalova (2013). Second, the frequency of capital inflows is quarterly rather than monthly.

In Table 8, we examine whether VRPs have predictive power for net capital inflows in 9 emerging markets. Panel A shows that local stock market returns and currency returns both positively predict net capital inflows in the future quarters. The coefficients on country-level VRP^i are also positive but insignificant, indicating no significant predictive power for future capital inflows.

[Insert Table 8 Here]

When we use VRP^{Global} in Panel B, the slope coefficients on VRP^{Global} are mostly positive and significant at the 5% level. Economically speaking, at the 1-quarter horizon, a 1% increase in monthly VRP^{Global} would lead to 3.51% increase in net capital inflows (as percent of GDP). At the 2-quarter horizon, the R^2 from the net capital inflow predictability regression on VRP^{Global} peaks at 11.8%, and decreases for longer horizons.

When we include both VRP^{EM} and VRP^{DM} in Panel C, the coefficients on VRP^{DM} are positive and significant at the 5% level at the 1-quarter horizon, while the coefficients on VRP^{EM} are positive and significant at the 5% level for all horizons longer than 2 quarters. The R^2 in Panel C is generally larger than those in Panel B, indicating that using both VRP^{EM} and VRP^{DM} obtains higher predictive power than only using VRP^{Global}. In summary, after controlling for both local stock market returns and currency returns, all VRP measures have significant predictive power for future capital inflows, with VRP^{Global} and VRP^{DM} more significant over shorter horizons, and VRP^{EM} more important over longer horizons. This pattern mirrors those of using VRPs for predicting stock market returns and currency returns in emerging markets reported in Section 3.1 and Section 3.2.

4 Robustness Check

In this section, we conduct robustness tests for the predictability of VRPs. First, we examine alternative estimation methods for predictive regressions. Second, we consider different ways to construct VRPs, and re-examine the predictive power. Third, we expand the predictability of VRPs to all MSCI developed and emerging markets.

4.1 Alternative Estimation Methods for Predictability

4.1.1 VRPs without Sample Extension

Constructing long-sample VRPs involves forward-looking information in the latter sample period. In order to test the predictability of extended VRPs without forward-looking information, we examine the predictive power of the real and observed VRP data without extending the sample. This leads to an unbalanced panel, because different markets have different lengths of observed time series data.

Table 9 provides the result for predictability of VRPs using unbalanced panel regressions in 9 emerging markets. For stock return predictability in Panel A, we find that the coefficients on VRP^{Global} are significant at the 5% level up to 12 months. When we include both VRP^{EM} and VRP^{DM}, the coefficients on VRP^{EM} are always significant after 4 months, while the coefficients on VRP^{DM} are significant up to 8 months.

[Insert Table 9 Here]

For currency return predictions in Panel B, VRP^{Global} is a significant predictor over all horizons. The coefficients on VRP^{EM} are significant at the 5% level after 9 months, while the coefficients on VRP^{DM} are significant over all horizons. The results for capital inflows in Panel C show similar patterns as in Panels A and B. Overall, the result confirms that, for the unbalanced observed sample, VRP^{Global}, VRP^{DM}, and VRP^{EM} are strong predictors for stock market returns, currency returns, and net capital inflows in emerging markets.

4.1.2 The Out-of-Sample Test for Predictability of VRPs

Our main results are based on the in-sample predictive regressions. We design the following out-of-sample test to examine the predictive power of VRPs in 9 emerging markets. First, using a sample over $[1, t-1]$, we estimate the panel regressions in equations (9), (11), and (12) and obtain the in-sample coefficients $\hat{b}_{h,t-1}$. Second, for time t, the out-of-sample predictor with the VRP is computed as $\hat{b}_{h,t-1}VRP_t$. Third, we repeat the above steps from $t = 60$ to T. Finally, using the market return predictability as an example, the out-of-sample estimation is modified from equation (9) as follows,

$$r^i_{t+1,t+h} = a_h + \rho(\hat{b}_{h,t-1}VRP_t) + CountryFE^i + \epsilon^i_{t+1,t+h}, \tag{13}$$

where we replace b_hVRP_t by $\hat{b}_{h,t-1}VRP_t$. If the in-sample fit of b_h is good, we expect to find ρ to be significantly different from zero and close to one.

The result in Appendix F Table F1 shows that VRP^{Global}, VRP^{DM}, and VRP^{EM} have significant predictive power for stock market returns, currency returns, and net capital inflows in the out-of-sample period, and ρ is most positive and significant. For the test of $\rho = 1$, we find the coefficients on VRP^{Global} are close to one for predicting these three variables over short horizons. The coefficients on VRP^{DM} are close to one for predicting stock returns and currency returns over short horizons. The hypothesis that the coefficients on VRP^{EM} are equal to one is not rejected when predicting currency returns and net capital inflows over long horizons. The out-of-sample test results show that the best performance for VRP^{Global} and VRP^{DM} is around 4 months, while it is at the 9-month horizon for VRP^{EM}.

4.1.3 The Predictability of VRPs Period by Period

In our main result above, we use VRPs to predict h-month ahead cumulative stock market returns, currency returns, or h-quarter ahead cumulative net capital inflows. To better pin down the horizon dynamics of the VRP measures, instead of using cumulative values from $t + 1$ to $t + h$ on the left hand side of the panel regressions in equations (9), (11), and (12), we use the VRP measures to predict stock market returns and currency returns over month $t + h$, and net capital inflows over quarter $t + h$.

The result is presented in Appendix F Table F2. The predictability of VRP^{Global} is significant at the 5% level up to 5 months. The predictability of VRP^{EM} is significant at the 5% level in 4-10 months, while the predictability of VRP^{DM} is significant at the 5% level in the first and third months. For predicting net capital inflows quarter by quarter, VRP^{Global} is significant in the first and second quarters. The predictability of VRP^{EM} is significant in 2-3 quarters, while VRP^{DM} has significant predictive power only in the first quarter. Compared with the predictability with cumulative returns in Tables 5 and 7, and cumulative net capital inflows in Table 8, we find that without the carryover from cumulative returns, the predictive horizon of VRPs is shorter. This is because cumulative measures have reduced some noise. But still, VRP^{EM} has strong predictive power over longer horizons, while VRP^{DM} has strong predictive power over shorter horizons.

4.2 Alternative Ways to Measure VRPs

4.2.1 Log VRPs

Realized variance and implied variance show positive skewness in Table 4. Some markets even have extreme large spikes during financial crisis, such as Russia. Alternatively, we can use the natural logarithm to deal with skewness in variance and huge spikes. The country-level log VRP is measured as the difference between the natural logarithm of implied variance and the natural logarithm of expected realized variance. The global, developed market, and emerging market log VRPs are the capitalization weighted average of country-level log VRPs. We test the predictability of the log VRPs in 9 emerging markets. The result is reported in Appendix F Table F3. Overall, we find that log VRP^{Global}, VRP^{DM}, and VRP^{EM} are still significant predictors for stock market returns, currency returns, and net capital inflows. Log VRP^{DM} has stronger predictive power in the shorter horizon, while log VRP^{EM} shows stronger predictive power in the longer horizon.

4.2.2 Equally Weighted VRPs

When aggregating VRPs using the market capitalization, the developed market VRP is dominated by the U.S., and the emerging market VRP is dominated by China. The U.S.

and China have dominant capitalizations in these two markets. Instead of using the value weighted scheme, we put equal weight on each market, and use the equally weighted scheme to construct the global, developed market, and emerging market VRPs. We use these three equally weighted VRPs to predict stock market returns, currency returns, and net capital inflows in 9 emerging markets.

The results are presented in Appendix F Table F4. The coefficients on VRP^{Global} are significant over all horizons for both stock and currency return predictability. The predictability of VRP^{EM} is significant for stock returns after 4 months, while its predictability for currency returns is weak over all horizons. This is due to the larger volatility of equally weighted VRP^{EM}. Variable VRP^{DM} shows significant predictive power for stock returns up to 7 months, and for currency returns over all horizons. For capital inflow predictability, VRP^{Global} is significant over all quarters. The coefficients on VRP^{EM} are significant after 2 quarters, while the coefficients on VRP^{DM} are not significant over all quarters. Overall, we find that these three equally weighted VRPs still have significant predictive power for stock market returns, currency returns, and net capital inflows.

4.3 Expanding the Predictability of VRPs to all MSCI Markets

4.3.1 Emerging Market and Developed Market VRPs

Our earlier results show that the global, developed market, and emerging market VRPs, as proxies for systematic uncertainty risk, significantly predict stock market return, currency returns, and capital flows in 9 major emerging markets or 11 developed markets. If these VRPs are truly important state variables, their predictive power should stay the same if we expand the sample to all MSCI markets. For the MSCI sample, we add 14 MSCI emerging markets (Chile, Colombia, Peru, Czech Republic, Egypt, Greece, Hungary, Qatar, Turkey, United Arab Emirates, Indonesia, Malaysia, Philippines, and Thailand), and 12 MSCI developed markets (Austria, Denmark, Finland, Ireland, Israel, Italy, Norway, Portugal, Spain, Sweden, New Zealand, and Singapore). In total, we have 46 markets, with 23 emerging markets and 23 developed markets. Data on MSCI country indices are collected from DataStream.

We investigate whether the value weighted global, developed market, and emerging market VRPs can still predict stock market returns, currency returns, and net capital inflows in all MSCI developed and emerging markets. The result is shown in Appendix F Tables F5, F6, and F7. We find that VRP^{Global}, VRP^{DM}, and VRP^{EM} are all significant predictors for stock market returns and currency returns in all MSCI emerging and developed markets. We also drop strictly regulated markets, such as China, HK, Qatar, and United Arab Emirates for currency return predictability. The result remains. Interestingly, for net capital inflow predictability, we find that the predictability of VRP^{Global} and VRP^{DM} disappears in all MSCI emerging and developed markets, while VRP^{EM} still has significant and positive coefficient for predicting capital inflows over horizons longer than 4 quarters.

4.3.2 Regional VRPs

It is conceivable that VRPs at a regional market might affect markets within the region. Therefore, we construct three regional VRPs for Americas, Asia-Pacific, Europe and Middle East. The Americas VRP (AM VRP) is the value weighted average of country-level VRPs across Canada, the U.S., Brazil, and Mexico. The Asia-Pacific VRP (AP VRP) is the value weighted average of country-level VRPs across Australia, HK, Japan, China, India, Korea, and Taiwan. The Europe and Middle East VRP (EU VRP) is the value weighted average of country-level VRPs across Belgium, France, Germany, the Netherlands, Switzerland, the U.K., Poland, Russia, and South Africa. As expected, the AM VRP is highly correlated with the global and developed market VRPs, while the AP and EU VRPs are more correlated with the emerging market VRP.

The results on predictive regressions in 46 MSCI emerging and developed markets using regional VRPs are reported in Appendix F Table F8. We find that regional VRPs can significantly predict stock market returns and currency returns even after controlling for the global VRP. For stock return predictability, the coefficients on the regional VRP are significant at the 5% level after 4 months. The regional VRP shows significant predictability for currency returns after 5 months. However, we do not find significant predictive power of regional VRPs for net capital inflows in all MSCI markets.

5 Conclusion

Many previous studies examine the VRP's predictive power for economic variables in developed market, yet studying the VRP in emerging markets has been difficult, because of the shortage of risk-neutral variance implied from index options. In this study, we first extend the sample of VRPs in 9 major emerging markets, using the sample-extension method in Lynch and Wachter (2013). Then we examine the predictive power of the emerging market VRP for stock market returns, currency returns, and capital inflows.

We find that the global VRP, the developed market VRP, and the emerging market VRP can significantly predict future equity market returns, currency returns, and net capital inflows. More interestingly, in all predictive regressions, the developed market VRP has a higher degree of predictability at the short horizon; while the emerging market VRP has stronger return predictability than the developed market VRP in the longer horizon. It is clear that the two VRPs contain different information. Furthermore, the joint return predictability of the emerging market VRP and the developed market VRP is stronger than the global VRP alone.

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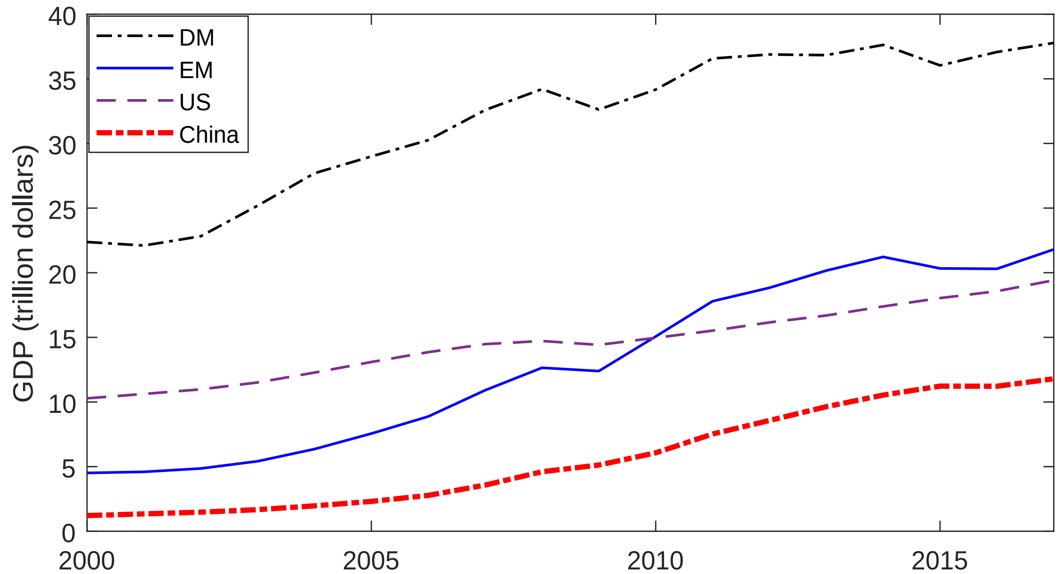
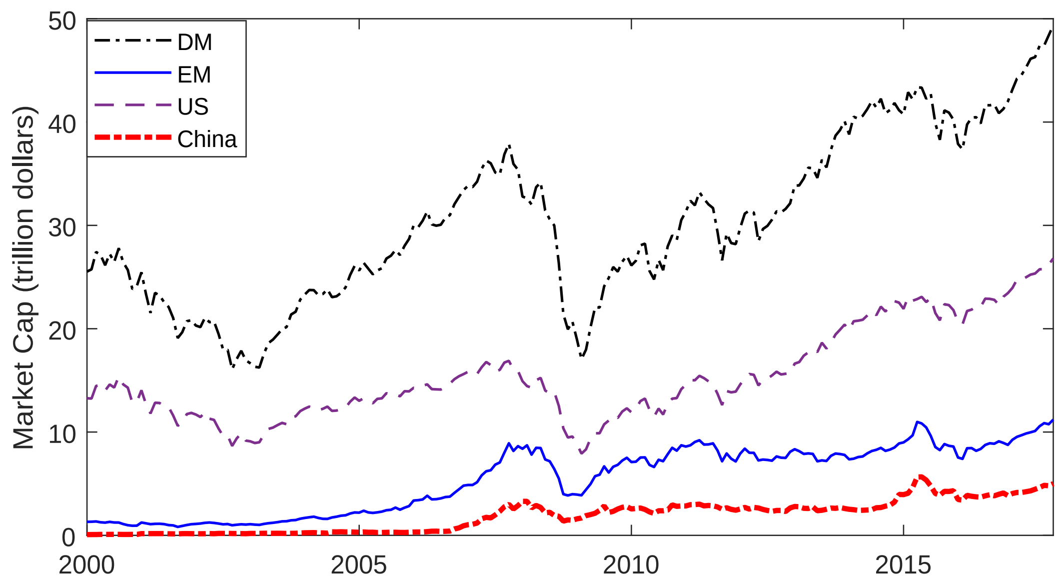


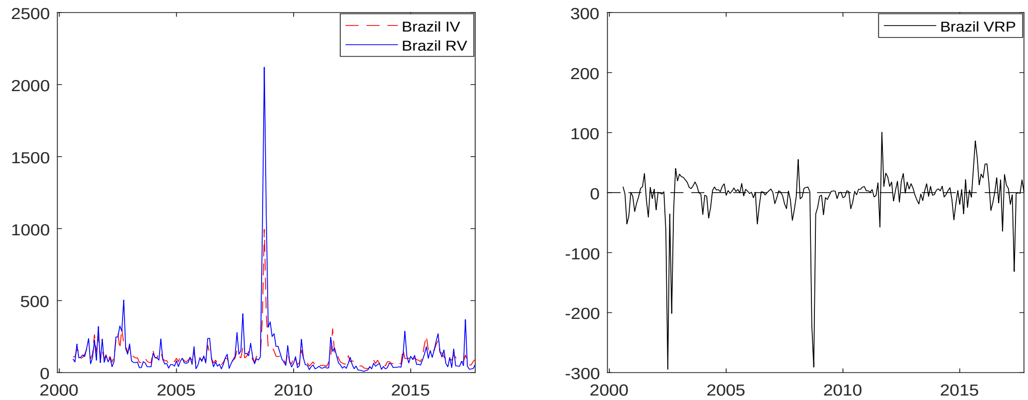
Panel A: GDP Level



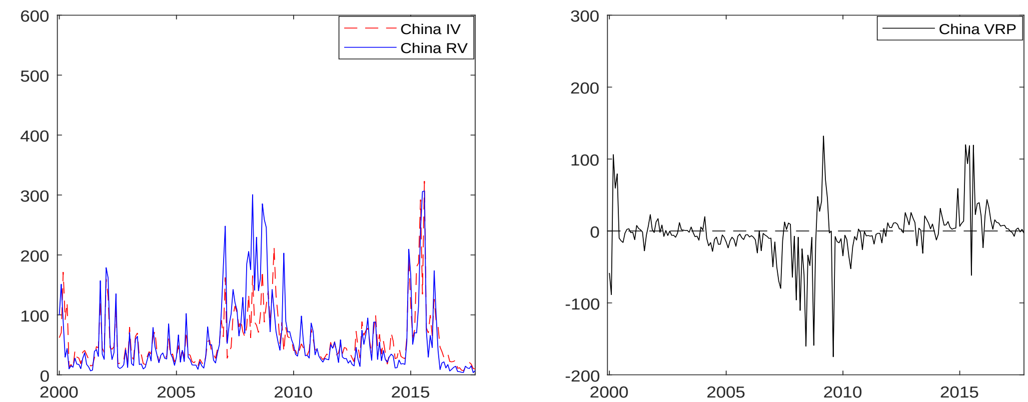
Panel B: Market Capitalization

Figure 1: GDP and Market Capitalization

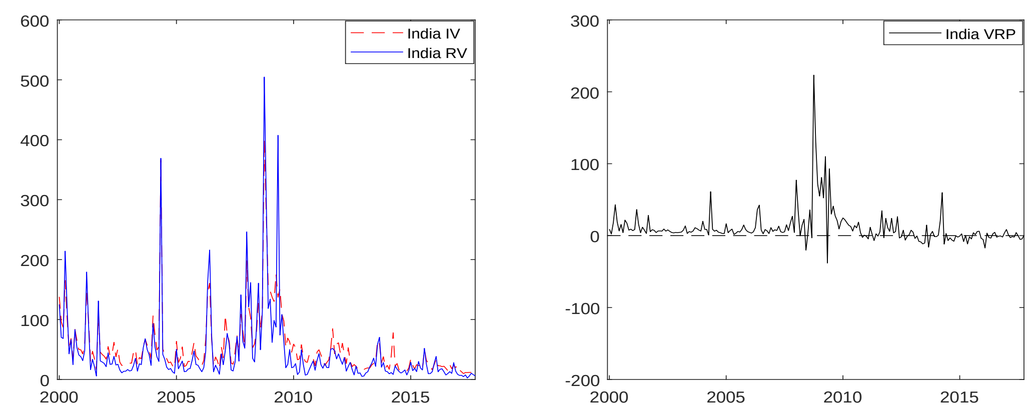
This figure plots the annual current price GDP and monthly market capitalization for developed markets (DM), emerging markets (EM), the U.S., and China from January 2000 to October 2017. The total market capitalization (GDP) in developed markets is the sum of market capitalization (GDP) in 11 developed markets: Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S.. The total market capitalization (GDP) in emerging markets is the sum of market capitalization (GDP) in 9 emerging markets: Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan.



Panel A. Brazil



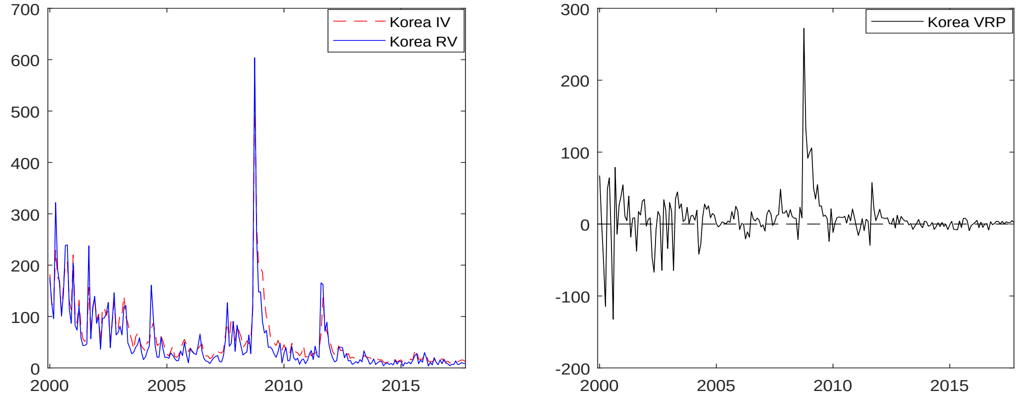
Panel B. China



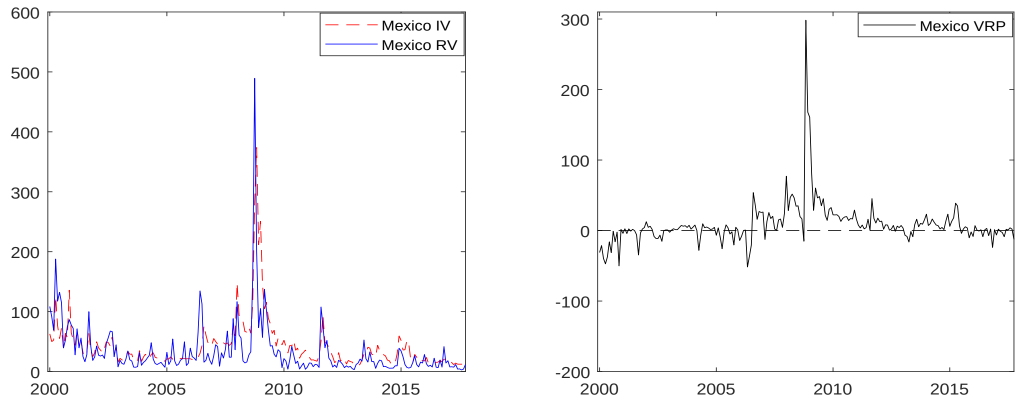
Panel C. India

Figure 2: Monthly Country-Level VRPs

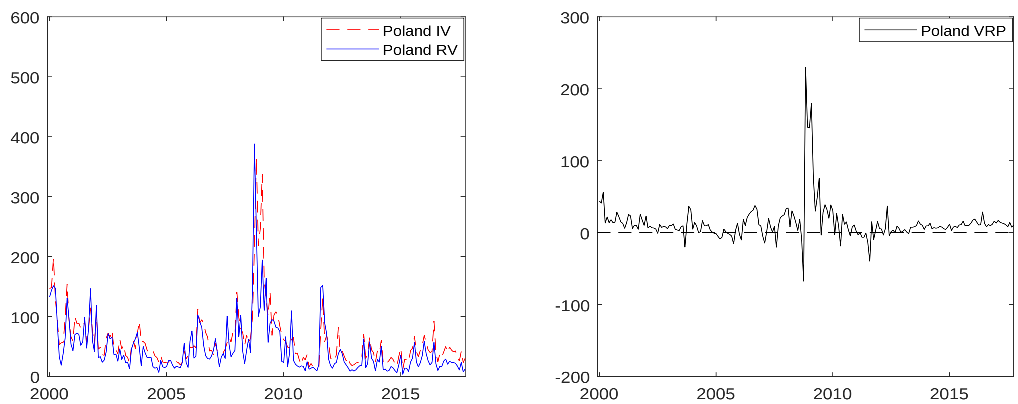
The figure shows the monthly country-level realized variance (RV), implied variance (IV), and VRPs on a monthly percentage-squared basis in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. The VRP is defined as the difference between the implied variance and the conditional expectation of future realized variance. The sample spans January 2000 to October 2017.



Panel D. Korea

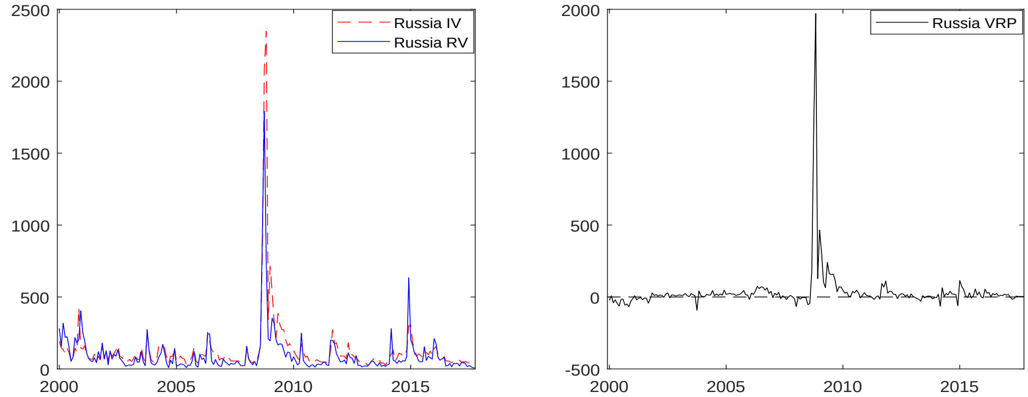


Panel E. Mexico

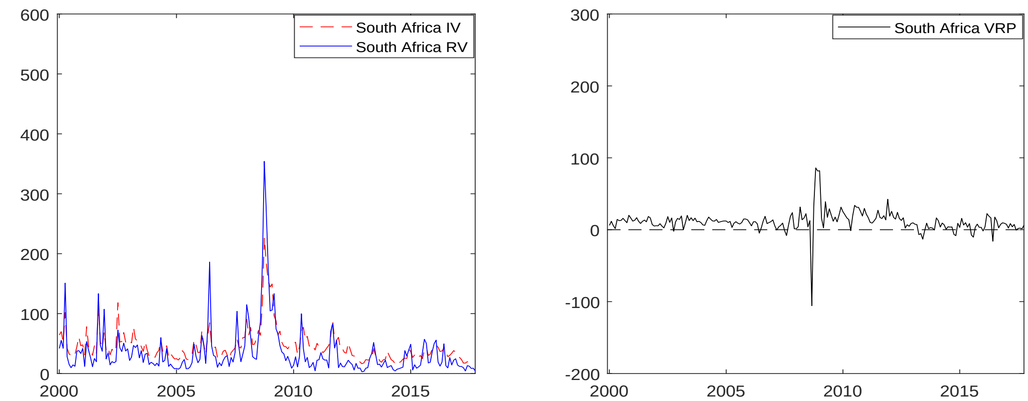


Panel F. Poland

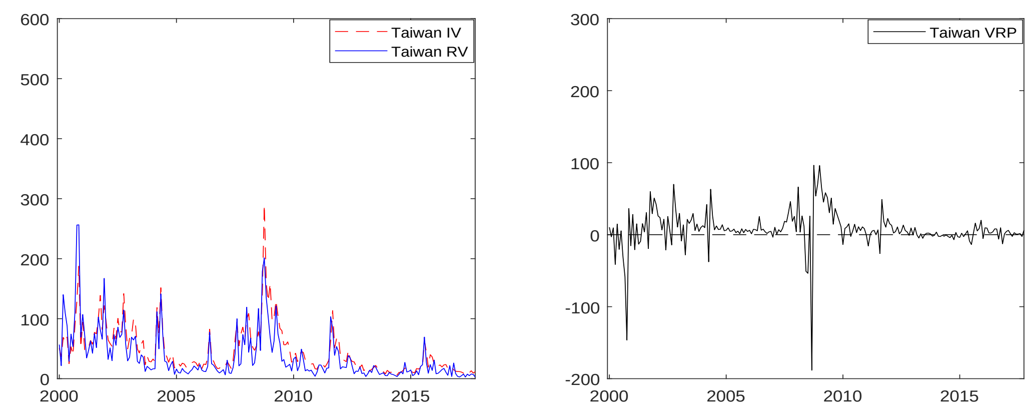
Figure 2: Monthly Country-Level VRPs—Continued



Panel G. Russia

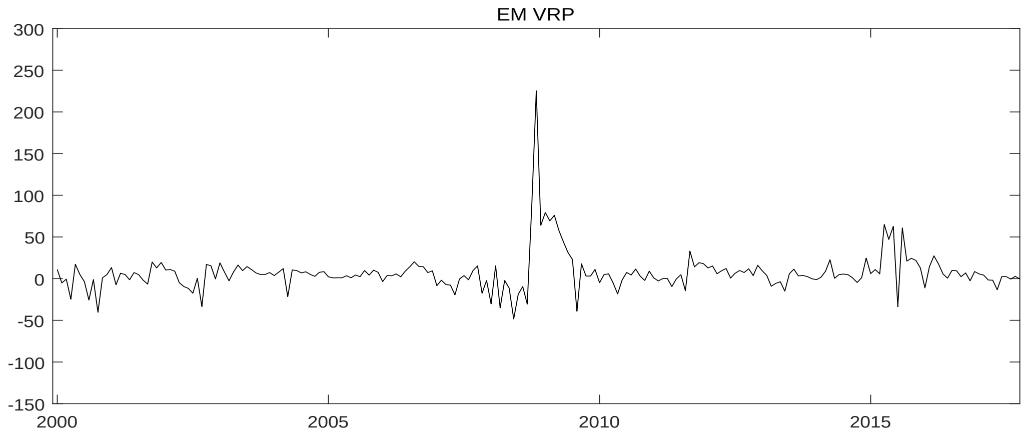


Panel H. South Africa

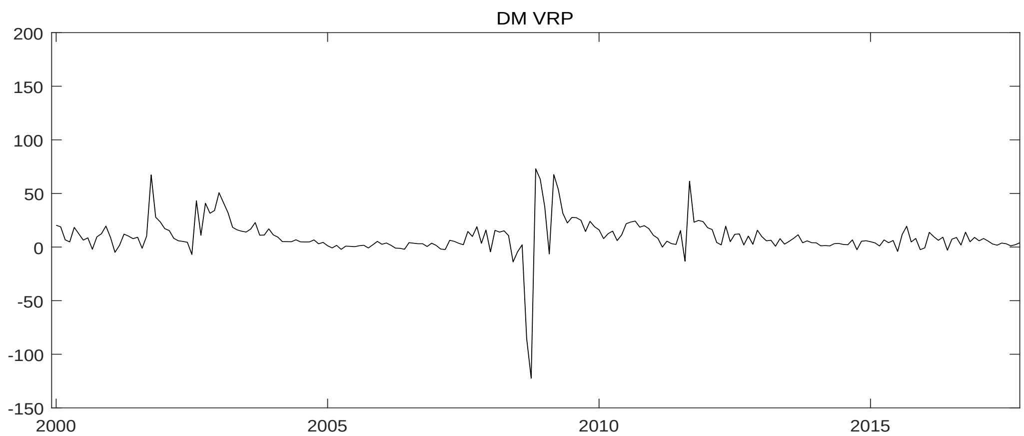


Panel I. Taiwan

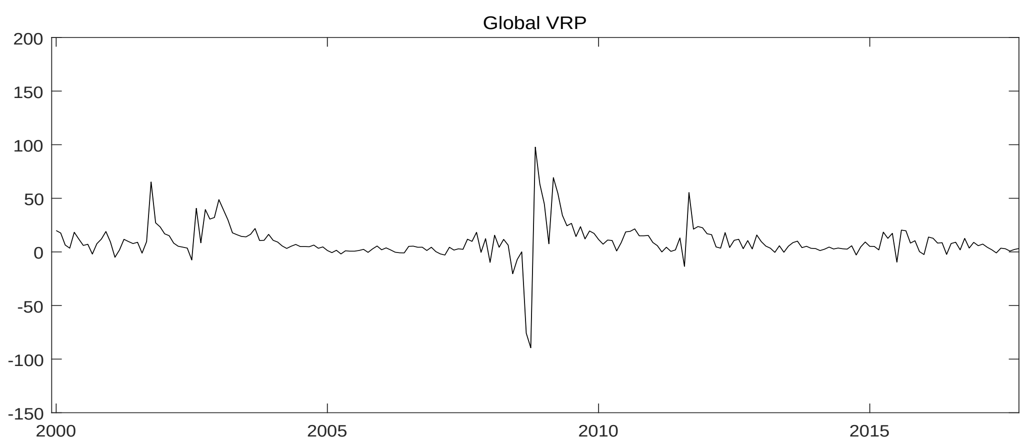
Figure 2: Monthly Country-Level VRPs—Continued



Panel A. EM VRP



Panel B. DM VRP



Panel C. Global VRP

Figure 3: Emerging Market, Developed Market, and Global VRPs

The figure shows the monthly emerging market (EM), developed market (DM), and global VRPs from January 2000 to October 2017. The VRP is defined as the difference between the implied variance and the conditional expectation of future realized variance on a monthly percentage-squared basis. The EM, DM, and global VRPs are the market capitalization weighted average of country-level VRPs across 9 emerging markets, 11 developed markets, and 20 international markets, respectively.

Table 1: Data

Market	Equity Index	Equity date	IV	IV date	IV Source
Panel A: Emerging Markets					
Brazil	EWZ ETF	200007	VXEWZ	201103	Datastream
China	SSE 50	199701	IVX	201502	Wind
India	Nifty 50	199604	INVIXN	200701	Bloomberg
Korea	KOSP 200	199001	VKOSPI	200301	Bloomberg
Mexico	Mexico IPC	198801	VIMEX	200403	Datastream
Poland	Wig 20	199406	VWIg20	200309*	Volatility Trading
Russia	RTS	199509	RTSVX*	200601	Datastream
South Africa	FTSE/JSE Top 40	199507	JSAVI	200702	Datastream
Taiwan	TAIEX	197101	TAIEX VIX	200712	Taiwan Futures Exchange
Panel B: Developed Markets					
Australia	S&P/ASX 200	199205	AXVI	200801	Datastream
Belgium	BEL 20	199001	VBEL	200001*	Datastream
Canada	S&P/TSX 200	198201	VIXC*	200212	Canada Derivatives Exchange
France	CAC 40	198707	VCAC	200001	Datastream
Germany	DAX	196501	V1X	199201	Datastream
HK	Hengsheng	196407	VHSI	200101	Bloomberg
Japan	Nikkei 225	195004	JNIV	199801	Datastream
Netherlands	AEX	198301	VAEX	200001	Datastream
Switzerland	SMI 20	198806	VSMI/V3X	199901	Datastream
UK	FTSE 100	198401	VFTSE	200001	Datastream
US	S&P 500	196401	VIX	199001	Datastream

Panel C: Macro Variables

	Brazil	China	India	Korea	Mexico	SA	Russia	Poland	Taiwan
CPI	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M
M1	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	Yes/M	No
UEMP	Yes/M	S(2002)/Q	S(2005)/A	Yes/M	Yes/M	Yes/M	Yes/M	S(2001)/Q	Yes/Q
EPU	Yes/M	Yes/M	S(2003)/M	Yes/M	Yes/M	No	Yes/M	No	No
rGDP	Yes/Q	Yes/Q	Yes/Q	Yes/Q	Yes/Q	Yes/Q	Yes/Q	Yes/Q	Yes/Q

Note: The table lists the implied volatility index, the corresponding underlying equity index in both developed and emerging markets, and the macroeconomic variables in emerging markets. Panels A and B provide the name, starting date for both implied volatility, and the corresponding underlying equity index as well as the data source for the implied volatility index. Panel C provides the availability and frequency of macroeconomic variables for 9 emerging markets. CPI is the seasonally adjusted CPI growth rate, M1 is the seasonally adjusted M1 growth rate, UEMP is the seasonally adjusted unemployment rate, EPU denotes the economic policy uncertainty index of Baker et al. (2016), rGDP is the seasonally adjusted real GDP growth rate. "Yes" means the macro data is available from 2000 to 2017, "No" means the macro data is not available, "S" means the macro data is available after 2000, and the starting date is shown in parentheses, M (Q and A) means the macro data is monthly (quarterly and annually). Note, Poland VWIg20 is no longer available after June 2013. Russia RSVX is no longer available after 9 December 2016, and it is changed to RVI index. Belgium VBEL is no longer available after November 2010. As for Canada, the implied volatility index is MVX from 2002 to 2009, and VIXC after 2009.

Table 2: Summary Statistics on Stock Market Returns

Panel A: Summary Statistics

	BRL	China	India	Korea	Mex	Pol	Russia	SA	TW	Austr	Belg	Cana	France	Germ	HK	Japan	Nether	Swiss	UK	US
Mean	0.11	0.09	0.14	0.08	0.13	0.04	0.17	0.12	0.03	0.04	0.03	0.05	0.01	0.06	0.06	0.03	0.01	0.03	0.02	0.05
StDev	0.36	0.29	0.23	0.22	0.18	0.24	0.35	0.18	0.22	0.13	0.16	0.14	0.18	0.21	0.21	0.19	0.19	0.13	0.13	0.15
Skew	-0.11	0.19	-0.22	-0.10	-0.26	0.17	-0.08	-0.09	0.19	-0.67	-1.11	-0.82	-0.46	-0.58	-0.35	-0.53	-0.83	-0.56	-0.57	-0.58
Kurt	3.49	5.22	4.85	4.04	3.89	4.03	4.11	3.38	4.92	3.46	6.18	5.30	3.62	5.23	3.89	3.72	5.15	3.67	3.67	4.23

Panel B: Correlation Matrix

	China	India	Korea	Mex	Pol	Russia	SA	TW	Austr	Belg	Cana	France	Germ	HK	Japan	Nether	Swiss	UK	US
BRL	0.31	0.58	0.57	0.62	0.55	0.63	0.58	0.53	0.58	0.54	0.70	0.57	0.56	0.69	0.39	0.58	0.45	0.64	0.65
China		0.28	0.27	0.21	0.26	0.20	0.26	0.30	0.33	0.25	0.28	0.24	0.27	0.48	0.27	0.25	0.23	0.23	0.28
India			0.59	0.53	0.55	0.41	0.53	0.52	0.56	0.52	0.56	0.50	0.52	0.65	0.54	0.54	0.44	0.53	0.54
Korea				0.61	0.55	0.49	0.62	0.67	0.57	0.51	0.60	0.56	0.60	0.61	0.53	0.60	0.49	0.58	0.62
Mex					0.58	0.59	0.55	0.52	0.57	0.51	0.66	0.55	0.58	0.58	0.48	0.58	0.49	0.57	0.65
Pol						0.47	0.50	0.47	0.54	0.49	0.56	0.61	0.59	0.59	0.48	0.58	0.49	0.59	0.59
Russia							0.53	0.54	0.47	0.43	0.63	0.48	0.45	0.55	0.45	0.46	0.38	0.53	0.57
SA								0.53	0.60	0.54	0.65	0.55	0.51	0.61	0.48	0.58	0.52	0.62	0.61
TW									0.50	0.49	0.55	0.51	0.52	0.60	0.46	0.54	0.39	0.51	0.55
Austr										0.71	0.65	0.71	0.65	0.64	0.59	0.69	0.63	0.72	0.73
Belg											0.61	0.83	0.77	0.57	0.52	0.84	0.75	0.78	0.73
Cana												0.67	0.63	0.69	0.55	0.67	0.58	0.70	0.77
France													0.92	0.61	0.59	0.91	0.79	0.85	0.82
Germ														0.62	0.58	0.87	0.75	0.80	0.80
HK															0.56	0.62	0.52	0.66	0.69
Japan																0.59	0.55	0.56	0.62
Nether																	0.78	0.83	0.79
Swiss																		0.74	0.74
UK																			0.84

Note: The table provides summary statistics and correlation matrix of monthly stock market returns across 20 markets from January 2000 to October 2017. These 20 markets include 9 emerging markets, which are Brazil (BRL), China, India, Korea, Mexico (Mex), Poland (Pol), Russia, South Africa (SA), Taiwan (TW), and 11 developed markets, which are Australia (Austr), Belgium (Belg), Canada (Cana), France, Germany (Germ), HongKong (HK), Japan, the Netherlands (Nether), Switzerland (Swiss), the U.K., the U.S.. Panel A reports the annualized mean, annualized standard deviation (StDev), skewness (Skew), and kurtosis (Kurt). Panel B reports the correlation matrix of monthly stock market returns.

Table 3: IV Extension

	Short Sample				Long Sample			
	$log(RV_{t+1})$		$log(IV_t)$		$log(RV_{t+1})$		$log(IV_t)$	
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
Panel A: Brazil								
Constant	1.85	4.00	2.37	11.94	1.76	6.60	2.36	10.77
$log(RV_t)$	0.44	4.16	0.39	8.71	0.51	8.26	0.40	9.15
Return1	0.11	0.36	-0.25	-1.66	-0.08	-0.37	-0.30	-2.06
Return5	-1.14	-1.41	-0.23	-0.72	-0.61	-1.48	-0.04	-0.16
Return21	-2.77	-2.41	-2.14	-4.02	-2.72	-3.28	-2.26	-4.45
CPI	0.21	0.65	0.17	1.44	-0.04	-0.34	0.08	1.78
M1	0.01	0.06	-0.04	-0.70	0.03	0.80	-0.02	-0.90
UEMP	-0.01	-0.20	0.03	1.92	0.03	1.71	0.03	3.20
EPU	0.12	1.02	0.03	0.88	0.01	0.10	0.01	0.29
rGDP	-0.09	-1.40	-0.04	-1.07	-0.03	-0.82	-0.03	-1.53
$adj.R^2$	39%		78%		43%			
Panel B: China								
Constant	1.81	3.72	1.59	4.33	1.07	4.52	1.63	6.10
$log(RV_t)$	0.52	4.90	0.74	9.12	0.68	12.97	0.70	9.33
$Return1$	-2.83	-1.84	-0.41	-0.40	0.16	0.53	0.50	2.01
$Return5$	-3.17	-2.52	0.87	1.46	0.17	0.26	0.34	0.47
$Return21$	-1.66	-0.57	0.99	0.67	-2.12	-2.09	1.49	1.69
CPI	-0.06	-0.18	-0.12	-0.86	-0.01	-0.11	-0.03	-0.35
M1	-0.03	-0.26	0.12	1.88	0.02	0.52	0.09	1.95
EPU	-0.29	-3.89	-0.02	-0.46	-0.09	-2.15	0.01	0.18
rGDP	0.19	1.26	-0.19	-1.99	0.07	1.85	-0.18	-3.04
$adj.R^2$	75%		90%		52%			
Panel C: India								
Constant	0.67	2.32	1.34	9.21	1.11	4.36	1.42	8.95
$log(RV_t)$	0.72	9.33	0.67	16.15	0.64	9.80	0.65	14.39
$Return1$	0.44	0.83	-0.06	-0.21	-0.06	-0.18	0.00	0.00
$Return5$	-2.63	-2.11	-1.05	-1.65	-2.22	-1.72	-1.59	-2.54
$Return21$	-1.88	-1.34	-0.20	-0.22	0.68	0.44	-0.35	-0.38
CPI	0.11	1.28	0.10	2.38	0.01	0.12	0.11	1.93
M1	0.01	0.86	0.01	1.45	0.01	0.71	0.01	1.06
rGDP	0.01	0.10	-0.01	-0.18	-0.01	-0.23	-0.02	-0.45
$adj.R^2$	58%		78%		43%			

Note: This table provides the GMM estimation results for realized variance and implied variance in 9 emerging markets using the sample-extension methodology of Lynch and Wachter (2013). The long sample period is from January 2000 to October 2017, during which realized variance is available in all markets. The short sample period is the available sample period of implied variance. For each market, the short sample period may be different. Variable $log(RV_t)$ denotes the natural logarithm of realized variance at the end of month t, $Return1$ is the downside daily return at the end of month t, $Return5$ denotes the downside weekly return at the end of month t, $Return21$ represents the downside monthly return in month t. We also include seasonally adjusted macro variables as explanatory variables (the choice may be different from market to market due to data availability), where CPI is the CPI growth rate, M1 denotes the M1 growth rate, rGDP is the real GDP growth rate, UEMP is the percent seasonally adjusted unemployment rate, EPU is the economic policy uncertainty index of Baker, Bloom, and Davis (2016) scaled by 100. In addition, CPI, M1, EPU, and UEMP are monthly data. rGDP is quarterly, which is forward filled the months within the quarter. In different columns, we report the coefficients, t statistics adjusted for White (1980) errors, and the adjusted R^2 for the short and long sample estimations.

Table 3: IV Extension—Continued

	Short Sample				Long Sample			
	$log(RV_{t+1})$		$log(IV_t)$		$log(RV_{t+1})$		$log(IV_t)$	
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
Panel D: Korea								
Constant	1.97	3.43	1.16	3.73	0.95	2.40	0.89	4.71
$log(RV_t)$	0.69	13.00	0.75	25.97	0.73	17.52	0.77	33.99
$Return1$	-0.45	-1.12	-0.03	-0.17	-0.67	-2.40	-0.06	-0.46
$Return5$	-3.26	-2.51	-0.56	-1.02	-2.43	-2.90	-0.45	-1.03
$Return21$	-0.42	-0.26	1.06	1.02	0.42	0.32	1.48	1.78
CPI	0.02	0.09	0.11	1.04	0.13	0.75	0.14	1.45
M1	0.06	2.39	-0.01	-0.33	0.06	2.76	0.00	-0.09
UEMP	-0.28	-1.61	0.01	0.16	-0.02	-0.15	0.08	1.59
EPU	-0.12	-1.97	-0.05	-1.20	-0.13	-2.13	-0.05	-1.22
rGDP	-0.04	-0.74	-0.05	-1.52	-0.03	-0.76	-0.04	-1.57
$adj.R^2$	57%		83%		66%			
Panel E: Mexico								
Constant	1.49	3.83	1.29	5.66	1.70	5.25	1.34	5.62
$log(RV_t)$	0.56	7.25	0.49	11.42	0.58	9.36	0.49	10.79
$Return1$	-0.43	-1.21	-0.52	-1.90	-0.30	-1.05	-0.55	-2.24
$Return5$	-0.91	-1.14	-0.55	-0.71	-1.34	-1.82	-0.42	-0.59
$Return21$	-6.02	-2.85	-1.80	-1.00	-4.23	-2.82	-2.23	-1.60
CPI	0.05	0.16	0.30	1.65	0.12	0.55	0.30	1.78
M1	-0.06	-0.79	-0.03	-0.68	-0.04	-0.67	-0.03	-0.64
UEMP	-0.07	-0.94	0.16	3.78	-0.12	-2.16	0.15	3.94
EPU	0.04	0.20	-0.06	-0.43	-0.05	-0.65	-0.07	-1.62
rGDP	-0.03	-0.50	-0.11	-2.37	-0.01	-0.28	-0.12	-2.48
$adj.R^2$	42%		56%		49%			
Panel F: Poland								
Constant	1.74	4.65	1.78	8.39	1.16	5.66	1.86	14.29
$log(RV_t)$	0.65	8.89	0.65	14.28	0.63	11.78	0.62	14.04
$Return1$	-0.10	-0.27	-0.04	-0.19	0.11	0.41	0.11	0.39
$Return5$	-0.62	-0.65	-0.76	-1.41	-0.86	-1.38	-1.10	-2.38
$Return21$	-0.49	-0.43	-0.57	-0.60	-2.15	-2.23	-0.55	-0.55
CPI	-0.31	-1.81	0.17	1.29	0.13	0.95	0.19	1.83
M1	-0.02	-0.42	-0.01	-0.42	-0.02	-0.55	-0.02	-0.63
UEMP	-0.04	-2.24	-0.02	-1.84	0.00	0.36	-0.02	-2.02
rGDP	0.08	1.03	-0.05	-0.97	0.00	0.04	-0.04	-0.71
$adj.R^2$	51%		75%		47%			

Table 3: IV Extension—Continued

	Short Sample				Long Sample			
	$log(RV_{t+1})$		$log(IV_t)$		$log(RV_{t+1})$		$log(IV_t)$	
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
Panel G: Russia								
Constant	1.49	4.31	1.55	9.88	1.95	5.77	1.63	8.25
$log(RV_t)$	0.49	6.64	0.56	10.68	0.53	9.06	0.56	12.98
$Return1$	-0.10	-0.31	-0.24	-1.37	-0.06	-0.34	-0.27	-2.10
$Return5$	-1.19	-1.72	0.07	0.19	-0.90	-1.87	0.04	0.11
$Return21$	-3.88	-3.53	-2.31	-3.76	-2.72	-3.07	-2.11	-3.18
CPI	0.03	0.29	-0.01	-0.20	0.03	0.37	-0.02	-0.33
M1	-0.03	-0.74	-0.09	-3.32	-0.02	-0.56	-0.09	-4.03
UEMP	0.23	1.64	0.39	6.88	0.00	0.01	0.35	6.72
EPU	-0.02	-0.27	0.02	0.52	-0.14	-1.86	0.00	0.05
rGDP	-0.02	-1.91	-0.01	-1.35	-0.01	-0.97	-0.01	-1.41
$adj.R^2$	52%		84%		43%			
Panel H: South Africa								
Constant	0.79	3.48	2.25	19.77	1.08	5.67	2.33	18.94
$log(RV_t)$	0.65	9.68	0.43	12.64	0.59	10.17	0.41	10.85
$Return1$	-0.34	-0.64	-0.14	-0.77	0.07	0.22	-0.14	-1.02
$Return5$	-1.48	-1.03	-0.68	-1.39	-2.08	-2.55	-0.75	-1.89
$Return21$	-5.37	-2.79	-2.57	-2.21	-3.84	-2.27	-2.86	-2.66
CPI	0.21	0.90	0.07	0.78	0.13	1.19	0.04	0.93
M1	0.02	0.56	-0.03	-1.68	0.03	0.85	-0.04	-2.26
rGDP	0.04	0.49	-0.04	-1.06	0.02	0.31	-0.03	-0.82
$adj.R^2$	53%		68%		44%			
Panel I: Taiwan								
Constant	0.57	1.49	0.36	2.08	0.80	2.81	0.39	2.33
$log(RV_t)$	0.61	6.65	0.70	16.69	0.65	12.45	0.72	22.58
$Return1$	0.37	0.42	-0.16	-0.47	-0.14	-0.38	-0.27	-1.62
$Return5$	-1.34	-0.83	0.22	0.28	-1.89	-2.02	0.20	0.45
$Return21$	-3.09	-1.36	0.76	0.69	-3.00	-2.31	1.31	1.58
CPI	0.07	0.63	0.16	2.59	0.12	1.42	0.18	3.68
UEMP	0.12	1.22	0.23	4.98	0.03	0.56	0.21	6.33
rGDP	-0.04	-1.47	-0.06	-3.36	-0.02	-1.12	-0.05	-3.20
$adj.R^2$	50%		82%		59%			

Table 4: Summary Statistics on VRPs

Panel A: Summary Statistics

	Implied Variance						Realized Variance					VRP				
	Obs	mean	StDev	Skew	Kurt	AR(1)	mean	StDev	Skew	Kurt	AR(1)	mean	StDev	Skew	Kurt	AR(1)
Emerging Markets																
Brazil	207	110.94	83.56	6.38	63.28	0.56	120.38	186.29	7.31	70.99	0.64	-5.58	42.24	-4.16	27.29	0.35
China	214	57.36	46.37	2.38	10.92	0.55	60.07	63.13	1.98	6.74	0.68	-2.48	36.69	-0.53	10.04	0.34
India	214	52.75	50.84	3.50	20.15	0.56	44.67	63.45	4.11	23.88	0.43	10.84	24.32	4.55	33.34	0.37
Korea	214	57.00	59.72	3.58	24.72	0.71	50.07	65.58	3.94	27.48	0.59	7.94	32.69	2.35	25.42	0.32
Mexico	214	42.02	42.06	4.37	28.31	0.82	33.97	45.96	5.40	47.87	0.59	8.86	31.45	4.80	40.21	0.59
Poland	214	59.13	46.94	3.25	17.80	0.78	46.12	45.40	3.13	18.91	0.65	13.69	27.36	4.38	30.76	0.52
Russia	214	128.07	225.91	7.81	71.53	0.68	97.94	159.52	6.83	65.12	0.62	34.67	164.44	9.41	102.31	0.52
SA	214	45.36	27.51	3.02	16.02	0.76	34.92	41.29	4.03	25.07	0.68	11.25	14.68	-0.67	27.71	0.38
Taiwan	214	46.23	39.09	2.11	10.10	0.75	37.54	41.61	2.43	10.61	0.66	7.75	27.23	-2.09	19.98	0.10
Developed Markets																
Australia	214	30.26	30.16	3.43	18.59	0.82	19.94	29.63	5.67	45.33	0.64	9.98	26.38	-6.59	88.34	0.11
Belgium	214	36.95	26.63	2.28	10.06	0.79	32.35	49.83	5.02	38.31	0.54	5.13	26.94	-7.21	71.72	0.42
Canada	214	31.17	32.82	4.14	23.63	0.83	27.57	51.71	6.73	60.95	0.69	5.01	19.08	0.02	18.11	0.46
France	214	49.40	41.26	2.73	12.67	0.76	43.58	59.50	4.79	37.03	0.61	6.06	25.77	-3.17	32.97	0.40
Germany	214	53.77	49.25	2.84	12.86	0.79	45.98	62.15	4.05	25.56	0.62	8.12	22.89	-0.40	12.37	0.06
HK	214	53.17	55.86	4.22	29.82	0.78	44.51	81.37	8.69	100.01	0.42	11.48	24.95	2.61	15.61	0.49
Japan	214	59.16	58.99	6.98	69.07	0.63	46.16	75.19	9.53	115.70	0.34	15.01	32.15	5.49	42.20	0.63
Nether	214	50.21	50.53	2.67	10.83	0.83	41.89	69.07	4.78	33.72	0.64	8.58	37.69	-7.50	91.38	0.29
Swiss	214	34.09	34.13	3.48	19.51	0.79	28.30	48.11	5.89	50.94	0.47	7.49	18.75	1.62	9.14	0.47
UK	214	37.01	33.91	2.64	11.94	0.82	28.81	46.98	6.19	56.33	0.59	8.17	28.24	-7.05	80.58	0.44
US	214	38.67	37.84	3.39	18.83	0.82	29.42	53.76	6.38	55.34	0.69	9.06	25.23	-6.18	72.37	0.22
EM, DM, and Global VRPs																
EM												7.08	23.90	4.11	35.69	0.46
DM												9.53	17.46	-1.68	22.89	0.36
Global												9.38	16.56	0.01	16.25	0.36

Note: This table reports summary statistics on monthly realized variance, extended implied variance, and extended VRPs for 9 emerging markets and 11 developed markets, as well as the emerging market (EM), developed market (DM), and global VRPs. The VRP is defined as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage-squared form. The sample period spans from January 2000 to October 2017. Panel A reports the observation (obs), mean, standard deviation (StDev), skew, kurtosis, and AR(1) coefficients. Panel B reports the correlation matrix for the global, DM, EM, and country-level VRPs. Note, implied variance and therefore VRPs are extended for all 9 emerging markets and 4 developed markets (Australia, Belgium, Canada, and HK).

Table 4: Summary Statistics on VRPs—Continued

Panel B: Correlation Matrix of VRP

	China	India	Korea	Mex	Pol	Russ	SA	TW	Austr	Belg	Cana	France	Germ	HK	Japan	Nether	Swiss	UK	US	EM	DM	Global
Brazil	0.20	-0.31	-0.23	0.08	0.09	-0.28	0.13	0.13	0.22	0.57	0.40	0.42	0.32	0.10	-0.30	0.45	-0.07	0.45	0.52	0.07	0.48	0.43
China		-0.16	-0.17	-0.02	0.17	-0.14	-0.04	0.06	-0.02	0.38	0.32	0.30	0.01	0.13	-0.09	0.15	-0.04	0.14	0.33	0.42	0.29	0.37
India			0.57	0.40	0.37	0.64	0.41	0.40	0.40	-0.30	0.00	-0.38	0.09	0.39	0.72	0.01	0.41	-0.04	-0.37	0.51	-0.06	0.07
Korea				0.39	0.31	0.57	0.35	0.42	0.34	-0.31	0.06	-0.35	0.22	0.41	0.70	-0.01	0.32	-0.06	-0.34	0.58	-0.03	0.09
Mex					0.71	0.63	0.53	0.30	0.35	0.20	0.52	-0.01	0.22	0.63	0.58	0.21	0.32	0.17	0.11	0.61	0.37	0.45
Pol						0.50	0.45	0.31	0.36	0.39	0.59	0.16	0.12	0.73	0.49	0.28	0.22	0.33	0.20	0.58	0.46	0.55
Russ							0.40	0.30	0.23	-0.25	0.17	-0.30	0.17	0.43	0.81	0.03	0.41	-0.08	-0.35	0.74	-0.01	0.16
SA								0.51	0.70	0.34	0.38	0.17	0.31	0.61	0.44	0.64	0.33	0.59	0.15	0.46	0.47	0.52
TW									0.67	0.22	0.44	0.11	0.33	0.51	0.45	0.54	0.39	0.51	0.06	0.52	0.39	0.45
Austr										0.38	0.41	0.05	0.19	0.55	0.40	0.71	0.30	0.69	0.08	0.38	0.42	0.45
Belg											0.60	0.70	0.17	0.38	-0.28	0.71	0.01	0.74	0.74	0.10	0.75	0.69
Cana												0.46	0.22	0.54	0.20	0.47	0.16	0.52	0.48	0.46	0.66	0.69
France													0.40	0.23	-0.35	0.61	0.25	0.62	0.74	-0.03	0.73	0.66
Germ														0.29	0.15	0.41	0.48	0.35	0.41	0.30	0.55	0.56
HK															0.51	0.45	0.38	0.48	0.22	0.58	0.55	0.62
Japan																0.06	0.45	0.03	-0.35	0.68	0.07	0.22
Nether																	0.37	0.90	0.49	0.27	0.72	0.71
Swiss																		0.28	0.12	0.40	0.39	0.46
UK																			0.59	0.18	0.80	0.77
US																				-0.01	0.87	0.78
EM																					0.31	0.51
DM																						0.97

Table 5: Stock Market Return Predictability in Emerging Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Panel A: Country-Level VRP														
VRP^i	0.01	0.01	0.02	0.05	0.07	0.09	0.08	0.07	0.07	0.07	0.07	0.07	0.04	0.04
	(0.15)	(0.20)	(0.35)	(1.10)	(1.86)	(3.14)	(3.10)	(3.03)	(3.18)	(3.93)	(4.49)	(4.56)	(2.90)	(2.65)
R^2	0.0%	0.0%	0.0%	0.5%	0.8%	1.6%	1.5%	1.3%	1.3%	1.6%	1.7%	1.6%	0.7%	0.7%
Panel B: EM VRP														
VRP^{EM}	0.39	0.35	0.31	0.39	0.44	0.48	0.46	0.44	0.42	0.41	0.38	0.36	0.21	0.21
	(3.53)	(3.06)	(2.92)	(4.43)	(5.92)	(6.61)	(6.81)	(6.85)	(7.05)	(6.95)	(6.75)	(6.73)	(5.29)	(5.45)
R^2	1.1%	1.6%	1.7%	3.6%	5.4%	7.3%	7.4%	7.5%	7.3%	7.5%	7.0%	6.6%	2.9%	3.4%
Panel C: DM VRP														
VRP^{DM}	1.07	0.70	0.56	0.63	0.53	0.42	0.28	0.22	0.14	0.12	0.11	0.11	0.01	0.08
	(6.53)	(5.42)	(5.77)	(7.52)	(6.62)	(5.49)	(4.02)	(3.09)	(1.84)	(1.68)	(1.50)	(1.60)	(0.21)	(1.31)
R^2	4.4%	3.4%	3.1%	5.0%	4.1%	3.0%	1.5%	1.0%	0.5%	0.4%	0.3%	0.3%	0.0%	0.3%
Panel D: Global VRP														
VRP^{Global}	1.12	0.77	0.64	0.73	0.65	0.57	0.43	0.36	0.28	0.26	0.23	0.23	0.09	0.16
	(6.16)	(5.26)	(5.61)	(7.53)	(7.27)	(6.44)	(5.46)	(4.57)	(3.29)	(3.18)	(2.99)	(3.09)	(1.41)	(2.39)
R^2	4.3%	3.7%	3.6%	5.9%	5.6%	4.8%	3.0%	2.4%	1.6%	1.5%	1.3%	1.3%	0.3%	0.9%
Panel E: EM and DM VRPs														
VRP^{EM}	0.16	0.21	0.20	0.28	0.36	0.43	0.44	0.43	0.43	0.42	0.40	0.37	0.23	0.21
	(1.61)	(2.00)	(1.96)	(3.25)	(4.82)	(5.87)	(6.13)	(6.26)	(6.76)	(6.84)	(6.54)	(6.36)	(5.26)	(5.14)
VRP^{DM}	1.00	0.61	0.48	0.51	0.38	0.24	0.10	0.04	-0.04	-0.06	-0.06	-0.05	-0.08	-0.01
	(6.23)	(5.05)	(5.00)	(6.33)	(4.82)	(3.41)	(1.39)	(0.50)	(-0.48)	(-0.77)	(-0.85)	(-0.63)	(-1.32)	(-0.15)
R^2	4.5%	3.9%	3.8%	6.6%	7.3%	8.1%	7.6%	7.5%	7.3%	7.6%	7.1%	6.7%	3.2%	3.4%

Note: The table provides the panel regressions of h-month ahead cumulative stock market index returns in local currency in annualized percentage unit on different VRPs in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are country-level VRPs, value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage-squared unit. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from January 2000 to October 2017.

Table 6: Stock Market Return Predictability in International Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Panel A: Country-Level VRP														
VRP^i	0.07	0.05	0.05	0.08	0.10	0.11	0.09	0.08	0.08	0.08	0.08	0.07	0.04	0.04
	(0.94)	(0.69)	(0.80)	(1.52)	(2.18)	(3.35)	(3.42)	(3.41)	(3.63)	(4.54)	(5.28)	(5.42)	(3.89)	(3.91)
R^2	0.2%	0.2%	0.2%	0.9%	1.4%	2.0%	1.8%	1.5%	1.5%	1.6%	1.6%	1.5%	0.8%	0.8%
Panel B: EM VRP														
VRP^{EM}	0.29	0.25	0.22	0.28	0.34	0.38	0.36	0.35	0.34	0.33	0.31	0.29	0.18	0.18
	(4.67)	(3.88)	(3.57)	(5.20)	(7.48)	(8.59)	(8.93)	(9.10)	(9.78)	(9.82)	(9.58)	(9.52)	(8.39)	(8.84)
R^2	0.9%	1.2%	1.3%	2.7%	4.7%	6.6%	6.8%	7.0%	7.3%	7.6%	7.1%	6.7%	3.5%	4.1%
Panel C: DM VRP														
VRP^{DM}	0.84	0.53	0.44	0.51	0.46	0.36	0.25	0.21	0.15	0.12	0.10	0.10	0.04	0.09
	(9.00)	(7.28)	(8.11)	(11.01)	(10.86)	(9.18)	(7.03)	(5.67)	(3.75)	(3.11)	(2.73)	(2.95)	(1.37)	(3.19)
R^2	4.0%	2.8%	2.9%	4.9%	4.6%	3.3%	1.8%	1.4%	0.8%	0.5%	0.4%	0.5%	0.1%	0.6%
Panel D: Global VRP														
VRP^{Global}	0.87	0.57	0.49	0.57	0.54	0.47	0.36	0.31	0.25	0.22	0.20	0.20	0.10	0.15
	(8.27)	(6.85)	(7.44)	(10.23)	(10.99)	(9.94)	(8.69)	(7.51)	(5.77)	(5.26)	(4.86)	(5.06)	(3.13)	(4.80)
R^2	3.8%	3.0%	3.1%	5.4%	5.8%	4.9%	3.2%	2.7%	2.0%	1.6%	1.4%	1.5%	0.5%	1.4%
Panel E: EM and DM VRPs														
VRP^{EM}	0.11	0.14	0.13	0.18	0.26	0.32	0.34	0.33	0.34	0.34	0.32	0.30	0.19	0.17
	(1.99)	(2.44)	(2.26)	(3.51)	(5.84)	(7.41)	(7.88)	(8.09)	(9.03)	(9.40)	(9.10)	(8.83)	(8.01)	(8.02)
VRP^{DM}	0.79	0.46	0.39	0.44	0.35	0.22	0.11	0.07	0.01	-0.03	-0.04	-0.02	-0.04	0.02
	(8.72)	(6.95)	(7.45)	(9.81)	(8.35)	(6.13)	(3.01)	(1.76)	(0.14)	(-0.71)	(-0.93)	(-0.53)	(-1.24)	(0.63)
R^2	4.1%	3.2%	3.3%	5.9%	7.1%	7.7%	7.1%	7.2%	7.3%	7.6%	7.1%	6.8%	3.6%	4.1%

Note: The table provides the panel regressions of h-month ahead cumulative stock market index returns in local currency in annualized percentage unit on different VRPs in 11 developed markets and 9 emerging markets. Predictors are country-level VRPs, value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the expectation of future realized variance in monthly percentage-squared unit. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from January 2000 to October 2017.

Table 7: Currency Return Predictability in Emerging Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Panel A: Country-Level VRP														
VRP^i	0.00	-0.02	-0.02	-0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01
	(-0.14)	(-0.89)	(-1.21)	(-0.38)	(0.15)	(0.59)	(0.70)	(0.66)	(0.52)	(0.86)	(1.18)	(1.26)	(1.19)	(1.35)
r_{LM}	0.05	0.04	0.04	0.03	0.03	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.01
	(3.12)	(4.04)	(4.25)	(4.01)	(3.76)	(3.86)	(3.73)	(3.02)	(3.02)	(3.40)	(3.30)	(3.70)	(4.66)	(4.59)
r_{US}	-0.02	-0.03	-0.02	-0.01	-0.01	-0.02	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-0.91)	(-1.65)	(-1.16)	(-1.06)	(-1.08)	(-1.66)	(-2.53)	(-1.72)	(-2.21)	(-2.27)	(-2.21)	(-2.70)	(-3.61)	(-3.77)
R^2	0.9%	1.3%	1.8%	1.5%	1.3%	1.3%	1.1%	0.7%	0.7%	0.9%	0.9%	1.2%	1.7%	2.0%
Panel B: Global VRP														
VRP^{Global}	0.42	0.23	0.21	0.30	0.28	0.24	0.21	0.17	0.15	0.15	0.13	0.12	0.09	0.11
	(4.05)	(2.89)	(3.74)	(6.07)	(6.29)	(6.16)	(5.76)	(4.79)	(4.74	(4.91	(4.55	(4.48	(3.95	(4.89
r_{LM}	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(2.17)	(3.21)	(3.43)	(3.08)	(2.86)	(3.09)	(2.87)	(2.07)	(2.01)	(2.40)	(2.37)	(2.77)	(3.60)	(3.18)
r_{US}	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	(-1.96)	(-2.24)	(-1.75)	(-2.35)	(-2.47)	(-2.89)	(-3.57)	(-2.64)	(-2.98)	(-2.98)	(-2.92)	(-3.38)	(-4.12)	(-4.50)
R^2	3.6%	2.7%	3.4%	6.4%	6.7%	6.2%	5.2%	3.8%	3.6%	3.9%	3.5%	3.7%	3.9%	6.3%
Panel C: EM and DM VRPs														
VRP^{EM}	-0.06	-0.05	-0.07	-0.01	0.03	0.06	0.07	0.07	0.07	0.08	0.07	0.07	0.05	0.05
	(-1.18)	(-0.96)	(-1.44)	(-0.37)	(0.92)	(1.72)	(2.05)	(2.01)	(2.23)	(2.82)	(2.84)	(2.87)	(2.82)	(3.49)
VRP^{DM}	0.48	0.27	0.26	0.31	0.25	0.19	0.15	0.11	0.09	0.08	0.07	0.06	0.05	0.06
	(5.58)	(4.29)	(5.31)	(6.84)	(6.54)	(5.45)	(4.23)	(3.23)	(2.91)	(2.55)	(2.19)	(2.11)	(1.84)	(2.45)
r_{LM}	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(2.31)	(3.36)	(3.72)	(3.29)	(2.87)	(2.96)	(2.64)	(1.83)	(1.75)	(2.07)	(2.07)	(2.47)	(3.34)	(2.98)
r_{US}	-0.06	-0.05	-0.04	-0.04	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-2.81)	(-3.07)	(-2.72)	(-3.05)	(-2.75)	(-2.97)	(-3.37)	(-2.31)	(-2.47)	(-2.33)	(-2.21)	(-2.56)	(-3.25)	(-3.60)
R^2	4.3%	3.3%	4.4%	7.1%	6.9%	6.4%	5.5%	4.2%	4.1%	4.8%	4.5%	4.6%	4.5%	7.1%

Note: The table provides the panel regressions of h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit on VRPs after controlling for local and U.S. stock returns in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are country-level VRPs, value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage-squared unit. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. Variables r_{LM} and r_{US} denote local and U.S. stock market returns, respectively. The sample period is from January 2000 to October 2017.

Table 8: Net Capital Inflow Predictability in Emerging Markets

h	1	2	3	4	5	6	7	8
				Panel A: Country-Level VRP				
VRP^i	-0.33	0.27	0.50	0.46	0.40	0.35	0.27	0.17
	(-0.26)	(0.31)	(0.75)	(0.83)	(0.85)	(0.81)	(0.64)	(0.42)
r_{LM}	0.06	0.05	0.04	0.02	0.02	0.01	0.01	0.01
	(2.54)	(2.83)	(2.48)	(1.91)	(1.78)	(1.48)	(1.39)	(1.22)
r_{FX}	0.07	0.05	0.03	0.00	0.01	0.00	0.01	0.01
	(1.77)	(1.81)	(1.00)	(0.18)	(0.28)	(0.09)	(0.33)	(0.64)
R^2	7.5%	7.0%	5.0%	2.7%	2.0%	1.4%	1.3%	1.2%
				Panel B: Global VRP				
VRP^{Global}	3.51	3.95	3.10	2.44	1.82	1.46	1.13	0.93
	(2.16)	(3.23)	(3.44)	(3.07)	(2.63)	(2.34)	(2.00)	(1.76)
r_{LM}	0.06	0.04	0.03	0.02	0.02	0.01	0.01	0.01
	(2.76)	(3.09)	(2.69)	(2.04)	(1.87)	(1.52)	(1.37)	(1.17)
r_{FX}	0.09	0.06	0.03	0.01	0.01	0.00	0.01	0.01
	(2.12)	(2.06)	(1.05)	(0.23)	(0.32)	(0.14)	(0.38)	(0.67)
R^2	10.0%	11.8%	8.6%	5.4%	3.8%	2.7%	2.2%	2.0%
				Panel C: EM and DM VRPs				
VRP^{EM}	-2.77	1.50	3.71	3.76	3.16	2.53	2.16	1.88
	(-1.73)	(1.27)	(2.93)	(3.18)	(2.94)	(2.52)	(2.35)	(2.20)
VRP^{DM}	5.30	2.75	0.34	-0.34	-0.52	-0.42	-0.46	-0.44
	(2.26)	(1.95)	(0.31)	(-0.31)	(-0.50)	(-0.42)	(-0.50)	(-0.51)
r_{LM}	0.06	0.04	0.02	0.01	0.01	0.01	0.01	0.01
	(2.90)	(2.66)	(1.90)	(1.19)	(1.04)	(0.86)	(0.82)	(0.65)
r_{FX}	0.07	0.07	0.05	0.02	0.02	0.01	0.02	0.02
	(1.81)	(2.20)	(1.60)	(0.86)	(0.98)	(0.70)	(0.93)	(1.15)
R^2	11.1%	12.0%	10.8%	8.5%	6.5%	4.7%	4.0%	3.5%

Note: The table provides the panel regressions of h-quarter ahead cumulative total net capital inflows (percent of GDP) on VRPs after controlling for quarterly local stock market and currency returns in percentage across 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are country-level VRPs, value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage unit. Net capital inflows are the difference between gross inflows and outflows. It provides the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. Variables r_{LM} and r_{FX} represent local stock returns and currency returns, respectively. The sample period is from Quarter 1, 2000 to Quarter 2, 2012.

Table 9: The Predictability of VRPs without Sample Extension in Emerging Markets

Panel A: Stock Market Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	1.15	0.75	0.61	0.71	0.64	0.56	0.41	0.34	0.25	0.24	0.22	0.22	0.07	0.14
	(5.91)	(4.93)	(5.17)	(7.13)	(6.78)	(5.91)	(4.85)	(3.92)	(2.74)	(2.59)	(2.47)	(2.58)	(1.02)	(1.91)
R^2	4.0%	3.1%	2.9%	5.0%	4.8%	4.1%	2.5%	1.9%	1.1%	1.1%	0.9%	1.0%	0.2%	0.7%
VRP^{EM}	-0.02	-0.03	-0.04	0.05	0.15	0.24	0.25	0.25	0.24	0.24	0.24	0.23	0.13	0.10
	(-0.19)	(-0.39)	(-0.56)	(0.81)	(2.42)	(3.68)	(3.94)	(3.89)	(4.31)	(4.47)	(4.38)	(4.33)	(2.92)	(2.04)
VRP^{DM}	1.02	0.63	0.54	0.65	0.52	0.40	0.26	0.21	0.14	0.11	0.09	0.08	-0.01	0.04
	(5.75)	(4.71)	(5.52)	(7.81)	(6.63)	(5.35)	(3.86)	(2.92)	(1.79)	(1.50)	(1.36)	(1.23)	(-0.25)	(0.64)
R^2	4.7%	3.1%	3.3%	5.9%	5.3%	5.2%	4.1%	3.8%	3.3%	3.4%	3.4%	3.2%	1.3%	1.0%

Panel B: Currency Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.44	0.23	0.20	0.29	0.28	0.24	0.20	0.16	0.15	0.14	0.13	0.12	0.09	0.11
	(4.07)	(2.76)	(3.51)	(5.93)	(6.20)	(6.10)	(5.62)	(4.57)	(4.44)	(4.54)	(4.26)	(4.21)	(3.80)	(4.71)
R^2	3.6%	2.6%	3.1%	5.9%	6.2%	5.8%	4.8%	3.4%	3.2%	3.5%	3.3%	3.4%	3.8%	6.2%
VRP^{EM}	-0.08	-0.10	-0.12	-0.07	-0.01	0.02	0.04	0.04	0.04	0.05	0.05	0.05	0.04	0.05
	(-1.40)	(-2.00)	(-2.90)	(-1.97)	(-0.47)	(0.79)	(1.25)	(1.31)	(1.47)	(2.17)	(2.45)	(2.60)	(2.84)	(3.24)
VRP^{DM}	0.53	0.30	0.29	0.35	0.29	0.23	0.18	0.14	0.12	0.11	0.09	0.08	0.05	0.06
	(5.43)	(4.20)	(5.57)	(7.60)	(7.60)	(6.76)	(5.66)	(4.50)	(4.58)	(4.39)	(3.91)	(3.71)	(2.71)	(3.56)
R^2	5.7%	4.6%	6.6%	9.4%	8.5%	7.0%	5.9%	4.1%	4.1%	4.6%	4.6%	4.7%	4.6%	7.2%

Note: The table provides the unbalanced panel regressions of stock market index returns, currency returns, and net capital inflows on VRPs without sample extension in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is not extended, and is defined as the difference between the implied variance and the conditional expectation of future realized variance. Panel A reports the result for predicting h-month ahead cumulative stock market returns in annualized percentage unit. Panel B reports the result for predicting h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit after controlling for both local and U.S. stock market returns. Panel C shows the result for predicting h-quarter ahead cumulative total net capital inflows (percent of GDP) after controlling for quarterly local stock market and currency returns in percentage. The VRPs are in monthly percentage-squared unit in Panels A and B, and in monthly percentage unit in Panel C. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2.

Table 9: The Predictability of VRPs without Sample Extension in Emerging Markets—Continued

Panel C: Net Capital Inflow Predictability

h	1	2	3	4	5	6	7	8
VRP^{Global}	3.87	4.12	3.06	2.40	1.81	1.48	1.16	0.94
	(2.17)	(3.18)	(3.23)	(2.81)	(2.39)	(2.14)	(1.84)	(1.59)
R^2	10.1%	11.5%	7.9%	4.8%	3.5%	2.5%	2.1%	1.9%
VRP^{EM}	-4.74	0.66	3.07	4.10	4.52	4.46	3.82	2.45
	(-1.54)	(0.29)	(1.33)	(1.78)	(2.15)	(2.32)	(2.08)	(1.39)
VRP^{DM}	5.13	3.78	2.10	1.24	0.47	0.21	0.17	0.32
	(2.24)	(2.51)	(1.93)	(1.21)	(0.54)	(0.27)	(0.24)	(0.51)
R^2	12.3%	12.4%	9.0%	6.5%	5.3%	5.4%	4.9%	2.9%

Appendix

A The Sample-Extension Methodology of Lynch and Wacher (2013)

Suppose T denotes the length of the long sample, and λT denotes the length of the short sample for $0 < \lambda \leq 1$. In our setting, the realized variance and predictive variables are observable in the long sample over $t = 0, ..., T$, while the implied variance is only observable in the short sample over $t = (1-\lambda)T, ..., T$. We start by considering a linear projection of the natural logarithm of realized variance on the space spanned by predictive variables that track the financial and economic conditions,

$$log(RV_{t+1}) = z_t\theta_1 + \varepsilon_{rv,t+1}, \tag{A.1}$$

where the 1 by J vector z_t includes a constant and $J-1$ predictors at time t, and θ_1 is the J by 1 vector of parameters. A similar projection is also defined for the natural logarithm of implied variance,

$$log(IV_t) = z_t\theta_2 + \varepsilon_{iv,t}. \tag{A.2}$$

Define the predictor matrices

$$Z_T = [z_0^\top, ..., z_{T-1}^\top]^\top, Z_{\lambda T} = [z_{(1-\lambda)T}^\top, ..., z_{T-1}^\top]^\top, \tag{A.3}$$

and similarly,

$$\begin{aligned} Y_{RV,T} =& [log(RV_1), ..., log(RV_T)]^\top, \\ Y_{RV,\lambda T} =& [log(RV_{(1-\lambda)T+1}), ..., log(RV_T)]^\top, \\ Y_{IV,\lambda T} =& [log(IV_{(1-\lambda)T}), ..., log(IV_{T-1})]^\top. \end{aligned} \tag{A.4}$$

Moment conditions are estimated using

$$\begin{aligned} g_{1,T}(\theta_1) =& \frac{1}{T}\sum_{t=0}^{T-1} f_1(z_t,\theta_1) = \frac{1}{T}Z_T^\top(Y_{RV,T} - Z_T\theta_1), \\ g_{1,\lambda T}(\theta_1) =& \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1} f_1(z_t,\theta_1) = \frac{1}{\lambda T}Z_{\lambda T}^\top(Y_{RV,\lambda T} - Z_{\lambda T}\theta_1), \\ g_{2,\lambda T}(\theta_2) =& \frac{1}{\lambda T}\sum_{t=(1-\lambda)T}^{T-1} f_2(z_t,\theta_2) = \frac{1}{\lambda T}Z_{\lambda T}^\top(Y_{IV,\lambda T} - Z_{\lambda T}\theta_2). \end{aligned} \tag{A.5}$$

where the 1 by J vector moment conditions $f_1(z_t,\theta_1) = (log(RV_{t+1}) - z_t\theta_1)z_t$ and $f_2(z_t,\theta_2) = (log(IV_t) - z_t\theta_2)z_t$.

Following Lynch and Wachter (2013), we conduct the GMM with unequal length of samples in four steps.

Step 1: We run the long-sample and short-sample time-series regression of $log(RV_{t+1})$ on predictors z_t in equation (A.1). We also run a short-sample time-series regression of $log(IV_t)$ on predictors z_t in equation (A.2). We obtain one long-sample estimated coefficient $\hat{\theta}_{1,T}$ and two short-sample estimated coefficients $\hat{\theta}_{1,\lambda T}$ and $\hat{\theta}_{2,\lambda T}$.

Step 2: We then run the short-sample time-series regression of each column in the λT by J vector moment conditions $f_2 (f_2 = \left[f_2(z_{(1-\lambda)T}, \hat{\theta}_{2,\lambda T})^\top, ..., f_2(z_{T-1}, \hat{\theta}_{2,\lambda T})^\top \right]^\top)$ on the λT by J vector moment conditions $f_1 (f_1 = \left[f_1(z_{(1-\lambda)T}, \hat{\theta}_{1,\lambda T})^\top, ..., f_1(z_{T-1}, \hat{\theta}_{1,\lambda T})^\top \right]^\top)$ on the λT in the short sample. The coefficients of these regressions are then collected in the corresponding row of a J by J matrix $\hat{B}_{21,\lambda T}$.

Step 3: We derive the long-sample moment conditions for the natural logarithm of implied variance,

$$g_{2,T}(\theta_2) = g_{2,\lambda T}(\theta_2) + \hat{B}_{21,\lambda T}(g_{1,T}(\theta_1) - g_{1,\lambda T}(\theta_1)). \tag{A.6}$$

The intuition behind this adjustment is quite straightforward. Consider, for example, the case where g_1 and g_2 are univariate. Now suppose that $g_{1,\lambda T}(\theta_1)$ in the short sample is higher than $g_{1,T}(\theta_1)$ in the long sample. Since g_1 and g_2 are positively correlated, $g_{2,\lambda T}(\theta_2)$ in the short sample is also likely to be higher than $g_{2,T}(\theta_2)$ in the long sample. Therefore, $g_{2,T}(\theta_2)$ is adjusted downward relative to $g_{2,\lambda T}(\theta_2)$ to produce the final estimate.

By construction in Step 1, we have $g_{1,T}(\hat{\theta}_{1,T}) = 0$. Then plugging the two short-sample moment conditions in equation (A.5) into equation (A.6), equation (A.6) is reduced to

$$g_{2,T}(\theta_2) = \frac{1}{\lambda T} Z_{\lambda T}^\top (Y_{IV,\lambda T} - Z_{\lambda T}\theta_2) - \hat{B}_{21,\lambda T} \left(\frac{1}{\lambda T} Z_{\lambda T}^\top (Y_{RV,\lambda T} - Z_{\lambda T}\hat{\theta}_{1,T}) \right). \tag{A.7}$$

Finally, by setting $g_{2,T}(\theta_2) = 0$, the adjusted estimated vector is given by

$$\hat{\theta}_{2,T} = (Z_{\lambda T}^\top Z_{\lambda T})^{-1} \left(Z_{\lambda T}^\top Y_{IV,\lambda T} - \hat{B}_{21,\lambda T} Z_{\lambda T}^\top (Y_{RV,\lambda T} - Z_{\lambda T}\widehat{\theta}_{1,T}) \right) = \hat{\theta}_{2,\lambda T} - A. \tag{A.8}$$

where A is the adjustment term given by $(Z_{\lambda T}^\top Z_{\lambda T})^{-1} \hat{B}_{21,\lambda T} Z_{\lambda T}^\top (Y_{RV,\lambda T} - Z_{\lambda T}\widehat{\theta}_{1,T})$.

Step 4: We use $\hat{\theta}_1 = \hat{\theta}_{1,T}$ and $\hat{\theta}_2 = \hat{\theta}_{2,T}$ as the final estimated coefficients, and show the distribution of these estimated coefficients $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2]$. We determine the properties of the J-vector of estimated coefficients $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2]$. Specifically, it is consistent and asymptotically normally distributed, i.e.

$$\sqrt{\lambda T}(\hat{\theta} - \theta) \sim N(0_{2J*1}, \Omega). \tag{A.9}$$

The $2J * 2J$ covariance matrix Ω is equal to

$$\Omega = (I_2 \otimes E[Z_T^\top Z_T]^{-1}) S^A (I_2 \otimes E[Z_T^\top Z_T]^{-1}), \tag{A.10}$$

where S^A is defined as

$$S^A = \begin{bmatrix} \lambda S_{11} & \lambda S_{12} \\ \lambda S_{21} & S_{22} - (1-\lambda) S_{21} S_{11}^{-1} S_{12} \end{bmatrix}. \tag{A.11}$$

To construct an estimate for S^A that makes use of the full sample, we apply the procedure outlined in Stambaugh (1997) and Lynch and Wachter (2013) for constructing a positive-definite variance-covariance matrix. We first use the White (1980) estimator to compute

$\hat{S}_{11}$ over the full sample. Second, we use the estimated coefficient matrix $\hat{B}_{21,\lambda T}$ and the estimated residual covariance matrix $\hat{\Sigma}$ from a regression of each column in the λT by J vector moment conditions $f_2(f_2 = \left[f_2(z_{(1-\lambda)T}, \hat{\theta}_{2,\lambda T})^\top, ..., f_2(z_{T-1}, \hat{\theta}_{2,\lambda T})^\top\right]^\top)$ on the λT by J vector moment conditions $f_1(f_1 = \left[f_1(z_{(1-\lambda)T}, \hat{\theta}_{1,\lambda T})^\top, ..., f_1(z_{T-1}, \hat{\theta}_{1,\lambda T})^\top\right]^\top)$ to compute the remaining terms:

$$\begin{aligned}\hat{S}_{12} =& \hat{S}_{11}\hat{B}_{21,\lambda T}^\top,\\ \hat{S}_{21} =& \hat{B}_{21,\lambda T}\hat{S}_{11},\\ \hat{S}_{22} =& \hat{\Sigma} + \hat{B}_{21,\lambda T}S_{11}\hat{B}_{21,\lambda T}^\top.\end{aligned} \tag{A.12}$$

This approach guarantees that the estimator of S^A is positive-definite. Plugging this estimator in equation (A.10) and replacing $E(Z_T^\top Z_T)$ with the estimated value over the long sample, we obtain a consistent estimator of Ω.

B CBOE Option-Implied Volatility Index

According to the CBOE white paper, the formula used in the VIX calculation is:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2, \tag{B.1}$$

where σ is $VIX/100$, T is time to expiration; F is forward index level desired from index option prices; K_0 is the first strike below the forward index level, F; K_i is strike price of the ith out-of-the-money option;[16] a call if $K_i > K_0$; and a put if $K_i < K_0$; both put and call if $K_i = K_0$. ΔK_i is the interval between strike prices—half the difference between the strike on either side of K_i: $\Delta K_i = \frac{K_{i+1} - K_i}{2}$. R is the risk-free interest rate to expiration, $Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike K_i.

The Mexico implied volatility index (VIMEX) measures the short-term (90 days calendar) implied volatility. The Poland volatility index is calculated following the original VIX methodology based on the most liquid at-the-money options, as in Whaley (1993). The South Africa implied volatility index (JSAVI) reflects the at-the-money volatilities and the volatility skew over 3-month horizon. The detail of the new JSAVI index is shown as follows.

In 2007, the new JSAVI was launched as an index designed to measure the market's expectation of the 3-month market volatility. In 2009, the Johannesburg Stock Exchange updated the JSAVI, which is calculated as the at-the-money volatility adjusted for the volatility skew as determined by the actively traded options in the market. The new JSAVI is not a polled volatility measurement. It is calculated as the weighted average prices of calls and puts over a wide range of strike prices, that expire in 3-months time. In short,

$$newJSAVI = \sqrt{\sum_{i=1}^{n=F} w_{ip}P_i(K_i) + \sum_{i=n}^{\infty} w_{ip}C_i(K_i)}. \tag{B.2}$$

[16] In-the-money options are less liquid.

Here F is the current (on value-date) forward of the FTSE/JSE Top40 index level, determined using the risk-free interest rate and dividend yield. F marks the price boundary between the liquid put options $P_i(K_i)$ and call options $C_i(K_i)$ with strikes K_i. The prices of call and put options are determined using the traded market volatility skew that expires in 3 months' time.

The 3-month (T) volatility skew $\sigma_K(0,T)$ is determined using the time weighted interpolation function (with N_1 and N_2 being the days to the near skew and next nearest skew, from the 3-month skew expiry date, respectively) defined by

$$\sigma_K(0,T) = \sqrt{\left\{T_2\sigma_K^2(0,T_2)\left[\frac{N_1}{N_2-N_1}\right] + T_1\sigma_K^2(0,T_1)\left[\frac{N_2}{N_2-N_1}\right]\right\}\frac{N_0}{N_3}}, \tag{B.3}$$

where N_0 is the number of days in the year (365 is the South African convention), and N_3 is the number of days from the value date to the 3-month date.

The weights used in equation (B.2) are that published by Derman et al. The Derman weightings are piecewise linear recurring option weightings.

$$w_{iP} = \frac{f(K_{i+1}) - f(K_i)}{K_i - K_{i+1}} - \sum_{j=0}^{i-1} w_{jP} \text{ and } w_{iC} = \frac{f(K_{i+1}) - f(K_i)}{K_i - K_{i+1}} - \sum_{j=0}^{i-1} w_{jC}, \tag{B.4}$$

where the log-contract is defined by $f(F_T) = \frac{2}{T}\left[\frac{F_T}{F_0} - log\frac{F_T}{F_0} - 1\right]$.

C The Out-of-Sample Test for Implied Variance Extension

We investigate whether the extended implied variance can fit the real implied variance well in the out-of-sample period. The out-of-sample period is the period of the first half of the sample with available implied variance. For example, the implied variance in Korea is available from January 2003, which is the earliest market. We assume that the implied volatility index is not available for Korea from January 2003 to December 2010, which is the out-of-sample period. Then we extend the implied variance from year 2010 to year 2000. Finally, we calculate the correlation between the extended implied variance and the real implied variance in the out-of-sample period from January 2003 to December 2010. We repeat the same procedure for the 8 out of our 9 emerging markets except China. Because China has a very short sample of implied variance, we will not conduct the out-of-sample test.

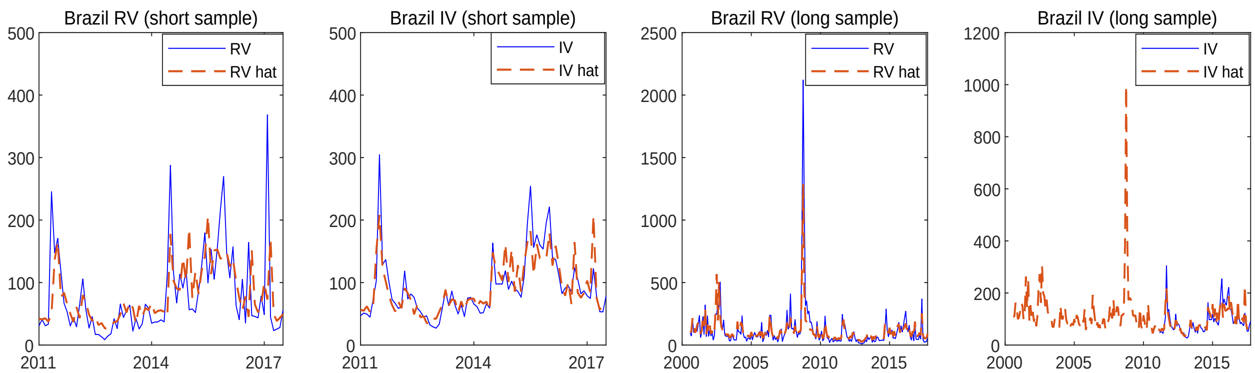
Table C1: The Out-of-Sample Test for Implied Variance Extension

	Brazil	India	Korea	Mexico	Poland	Russia	South Africa	Taiwan
OOS Period	201103-	200701-	200301-	200403-	200309-	200601-	200702-	200712-
	201312	201112	201012	200812	200812	201112	201112	201212
correlation	0.87	0.84	0.89	0.67	0.73	0.72	0.89	0.69

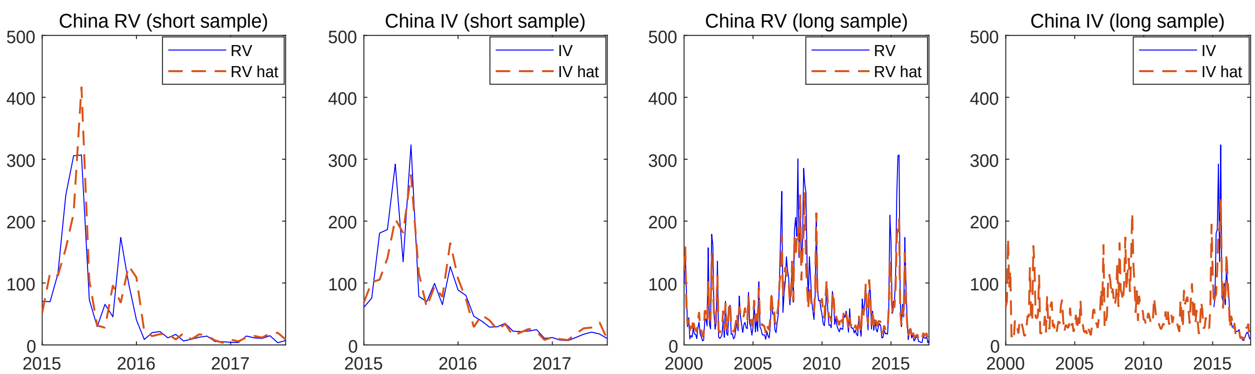
Note: This table provides the out-of-sample (OOS) test for implied variance extension in 8 emerging markets except for China. For each market, we assume the first half of the implied variance data is missing, which is the out-of-sample period. Then we do the sample extension for implied variance to year 2000 based on the latter half of the implied variance data. We calculate and report the correlation between the extended implied variance and the real implied variance in the out-of-sample period.

D The Fit of Implied Variance and Realized Variance in the Short and Long Samples

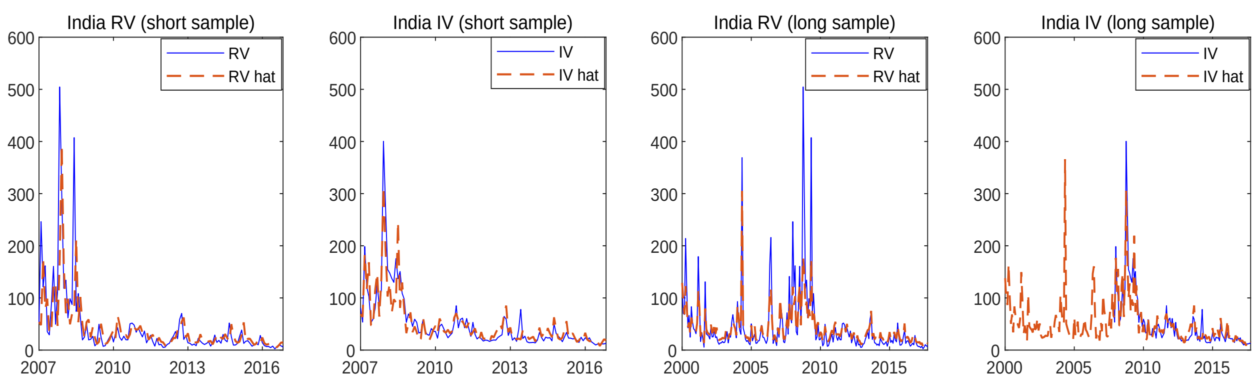
The figures plot the real value of realized variance (RV) and implied variance (IV), and the fitted value of RV and IV for 9 emerging markets in short and long samples, respectively. The fitted values of RV and IV are from the GMM estimation following Lynch and Wachter (2013). The short sample period is the sample period of IV, and the long sample period is the sample period of RV from January 2000 to October 2017.



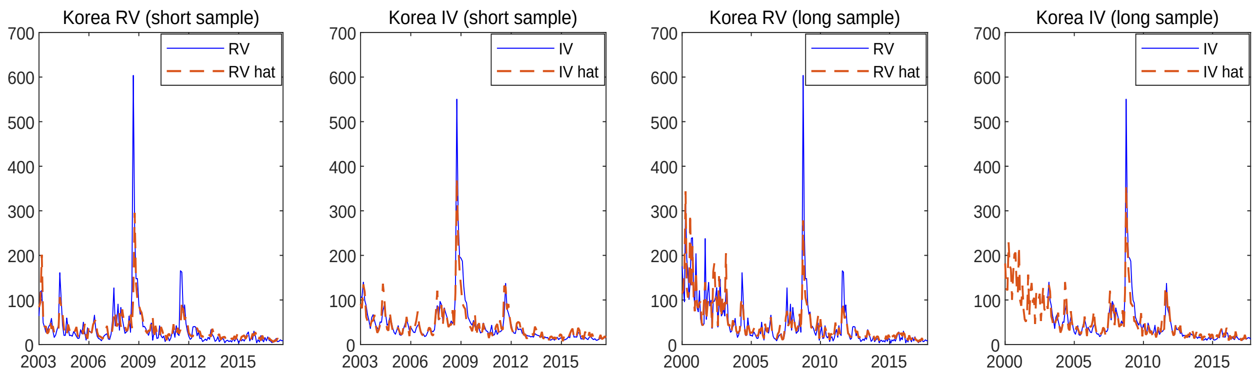
Panel A. Brazil



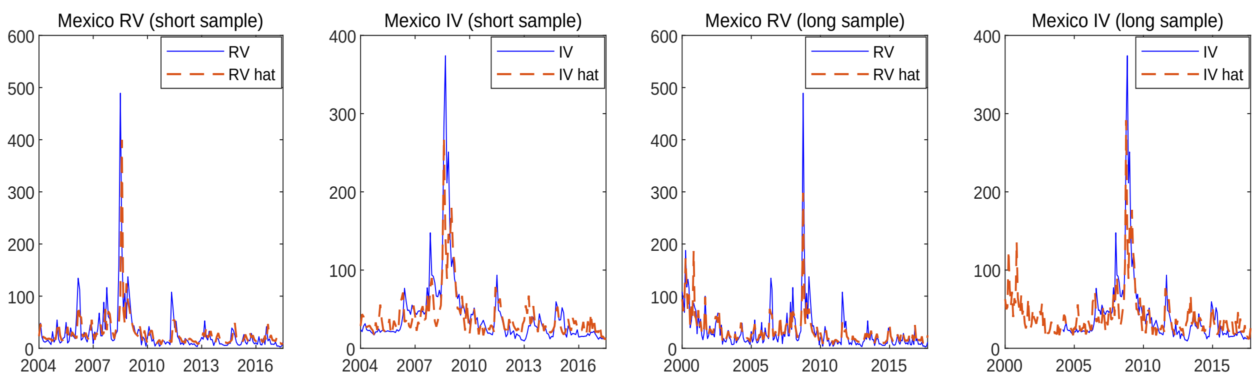
Panel B. China



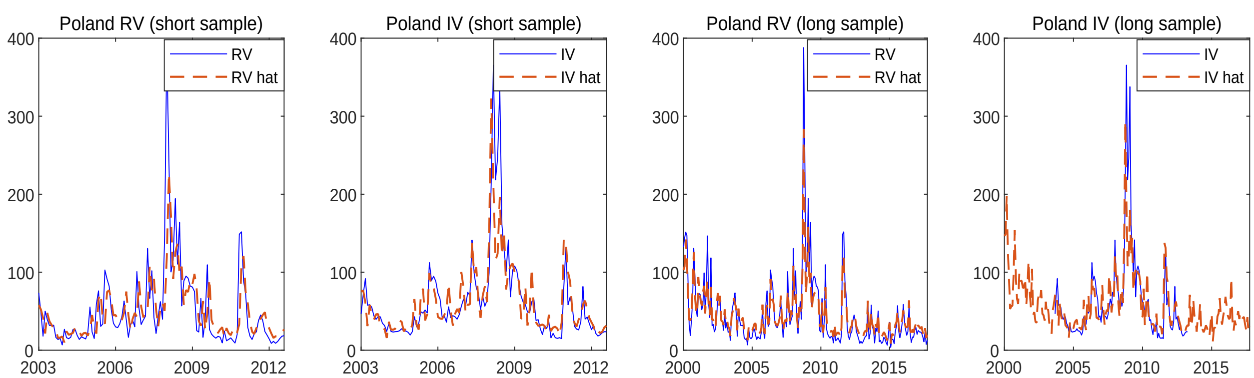
Panel C. India



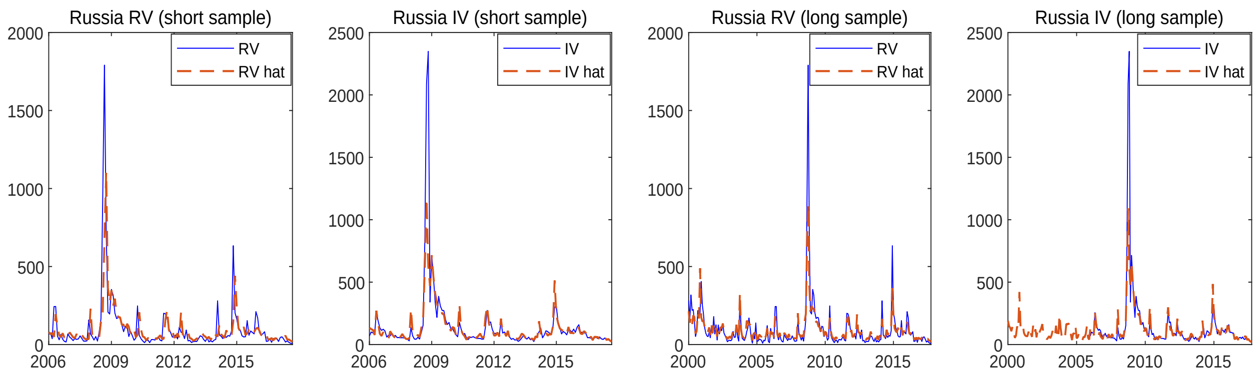
Panel D. Korea



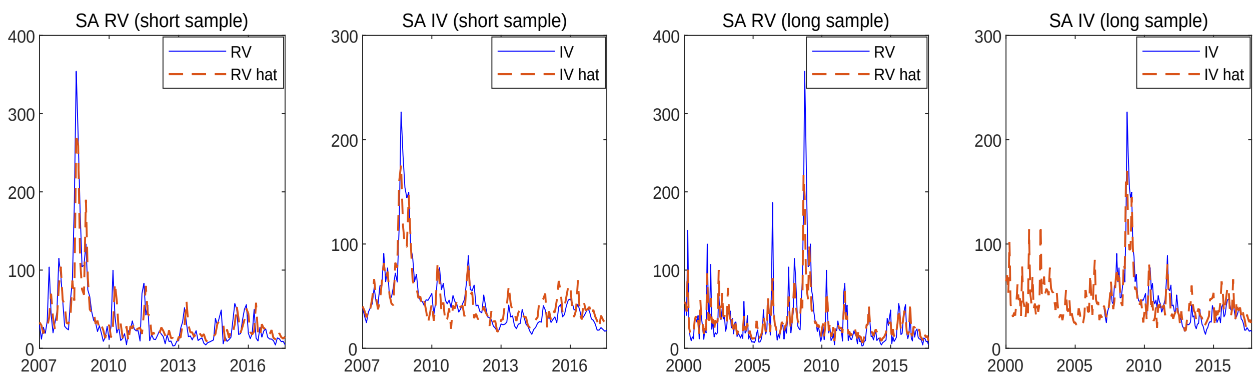
Panel E. Mexico



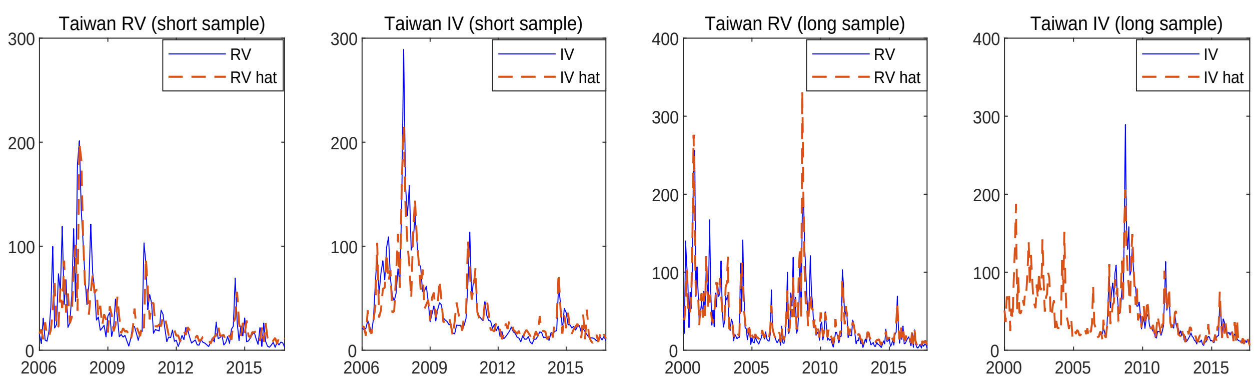
Panel F. Poland



Panel G. Russia



Panel H. South Africa



Panel I. Taiwan

E The Joint Predictability of VRPs

Table E1: Joint Stock Market Return Predictability of VRPs in Emerging Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Panel A: Global and Country-Specific VRPs														
VRP^{Global}	1.12	0.77	0.64	0.73	0.65	0.57	0.43	0.36	0.28	0.26	0.23	0.24	0.09	0.16
	(6.22)	(5.26)	(5.61)	(7.51)	(7.25)	(6.44)	(5.49)	(4.61)	(3.32)	(3.21)	(3.03)	(3.11)	(1.42)	(2.40)
$VRP^{specific}$	-1.73	0.07	-0.06	0.90	1.72	2.59	2.88	2.26	2.52	2.62	2.52	2.11	1.37	0.99
	(-0.68)	(0.03)	(-0.03)	(0.57)	(1.17)	(1.64)	(1.74)	(1.41)	(1.60)	(1.68)	(1.58)	(1.38)	(1.11)	(0.90)
R^2	4.3%	3.7%	3.6%	6.0%	5.8%	5.2%	3.6%	2.8%	2.1%	2.0%	1.8%	1.7%	0.5%	1.1%
Panel B: EM, DM and Country-Specific VRPs														
VRP^{EM}	0.16	0.21	0.20	0.28	0.36	0.43	0.44	0.44	0.43	0.42	0.40	0.37	0.23	0.21
	(1.66)	(2.06)	(2.03)	(3.31)	(4.87)	(5.87)	(6.13)	(6.26)	(6.72)	(6.78)	(6.49)	(6.30)	(5.21)	(5.02)
VRP^{DM}	1.00	0.60	0.48	0.51	0.38	0.24	0.10	0.04	-0.04	-0.06	-0.06	-0.05	-0.08	-0.01
	(6.24)	(5.05)	(5.02)	(6.37)	(4.83)	(3.41)	(1.38)	(0.49)	(-0.49)	(-0.78)	(-0.85)	(-0.64)	(-1.33)	(-0.16)
$VRP^{specific}$	-2.54	-1.58	-1.54	-0.93	-0.82	-0.50	-0.48	-1.19	-0.96	-0.78	-0.61	-0.78	-0.43	-0.72
	(-1.03)	(-0.71)	(-0.85)	(-0.61)	(-0.58)	(-0.39)	(-0.36)	(-0.92)	(-0.75)	(-0.66)	(-0.53)	(-0.72)	(-0.44)	(-0.87)
R^2	4.6%	3.9%	3.9%	6.6%	7.3%	8.1%	7.6%	7.6%	7.4%	7.7%	7.1%	6.8%	3.2%	3.5%

Note: The table provides the joint panel regressions of h-month ahead cumulative stock market returns in local currency in annualized percentage unit on different VRPs in 9 emerging markets. Predictors include the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance, which is denoted in monthly percentage-squared unit. We add the country-specific VRPs in the regression, which are the residuals from the time-series regressions of the country-level VRPs on the global VRP, or both the EM and DM VRPs, respectively. It provides the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from January 2000 to October 2017.

F Robustness Check

Table F1: The Out-of-Sample Test for Predictability of VRPs in Emerging Markets

Panel A: Stock Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Predictors: Global VRP														
$\rho(VRP^{Global})$	0.75	0.54	0.70	1.14	1.35	1.44	1.43	0.56	-0.69	-0.33	-0.87	0.26	-0.41	0.09
$\rho = 0$	(3.97)	(2.14)	(2.55)	(4.46)	(4.92)	(3.67)	(2.53)	(0.69)	(-0.74)	(-0.32)	(-0.83)	(0.21)	(-0.59)	(0.09)
$\rho = 1$	(-1.30)	(-1.84)	(-1.08)	(0.56)	(1.29)	(1.12)	(0.77)	(-0.55)	(-1.80)	(-1.26)	(-1.78)	(-0.59)	(-2.05)	(-0.90)
R^2	3.3%	1.7%	2.0%	5.1%	5.5%	4.5%	2.4%	0.2%	0.3%	0.1%	0.4%	0.0%	0.6%	0.0%
Predictors: EM and DM VRPs														
$\rho1(VRP^{EM})$	0.13	-0.08	0.01	0.30	0.49	0.62	0.59	0.62	0.65	0.60	0.61	0.62	0.59	0.83
$\rho1 = 0$	(1.00)	(-0.67)	(0.07)	(2.00)	(3.09)	(4.49)	(4.09)	(4.30)	(4.41)	(4.19)	(4.77)	(5.23)	(4.24)	(5.10)
$\rho1 = 1$	(-6.63)	(-9.50)	(-9.78)	(-4.66)	(-3.22)	(-2.70)	(-2.81)	(-2.67)	(-2.42)	(-2.77)	(-3.10)	(-3.20)	(-2.89)	(-1.03)
$\rho1(VRP^{DM})$	0.72	1.00	1.71	0.98	0.61	0.18	0.17	0.19	0.26	0.37	0.39	0.50	0.26	0.47
$\rho2 = 0$	(4.09)	(2.31)	(3.33)	(1.78)	(1.01)	(0.31)	(0.52)	(0.68)	(1.23)	(1.54)	(1.77)	(1.72)	(1.46)	(2.10)
$\rho2 = 1$	(-1.63)	(0.00)	(1.39)	(-0.03)	(-0.64)	(-1.47)	(-2.52)	(-2.85)	(-3.46)	(-2.60)	(-2.82)	(-1.71)	(-4.09)	(-2.35)
R^2	2.3%	1.5%	2.4%	3.6%	7.7%	11.7%	13.0%	13.8%	14.4%	13.4%	13.1%	12.5%	14.3%	28.0%

Note: This table provides the result for panel regressions of real values on predicted values in the out-of-sample period for 9 emerging markets. We first use VRPs to predict returns in the in-sample period over $[1, t-1]$ (at least 60 observations for stock and currency returns, 30 observations for net capital inflows). The VRPs include the value weighted emerging market (EM), developed market (DM), and global VRPs. We obtain the estimated parameters on VRPs, and then predict stock returns, currency returns, or capital inflows in the next period. We repeat these steps recursively from t to T. Finally, we run panel regressions of real returns on predicted returns. Panel A (B) reports the out-of-sample test result for cumulative stock return (currency return) predictability. Panel C shows the out-of-sample test result for cumulative net capital inflow predictability. It provides the coefficients, ρ, on predicted values, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. Note, $\rho(VRP^{Global})$ is the coefficient of regressing real values on predicted values of the global VRP (estimated coefficients $*VRP^{Global}$). Variables $\rho1(VRP^{EM})$ and $\rho2(VRP^{DM})$ are the coefficients of regressing real values on predicted values of EM and DM VRPs (estimated coefficients $*VRP^{EM}$ and coefficients $*VRP^{DM}$), respectively. The $\rho = 0$ and $\rho = 1$ rows represent the t-statistics for testing whether the coefficients, ρ, are significant and equal to 1, respectively.

Table F1: The Out-of-Sample Test for Predictability of VRPs in Emerging Markets—Continued

Panel B: Currency Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Predictors: Global VRP, Local, and U.S. Stock Returns														
$\rho(VRP^{Global})$	1.02	0.10	0.59	1.29	1.48	1.65	1.85	1.58	1.37	1.77	0.71	0.89	2.52	1.62
$\rho = 0$	(2.93)	(0.20)	(1.20)	(3.81)	(5.64)	(5.66)	(4.77)	(2.81)	(2.02)	(2.40)	(0.90)	(1.15)	(2.58)	(2.41)
$\rho = 1$	(0.05)	(-1.86)	(-0.83)	(0.87)	(1.82)	(2.23)	(2.19)	(1.03)	(0.54)	(1.05)	(-0.37)	(-0.14)	(1.56)	(0.92)
R^2	2.0%	0.0%	0.7%	4.9%	5.7%	6.0%	5.0%	2.8%	1.4%	1.9%	0.2%	0.3%	4.4%	13.6%
Predictors: EM, DM VRPs, Local, and U.S. Stock Returns														
$\rho1(VRP^{EM})$	-1.90	-2.06	-0.79	-0.12	0.32	0.65	0.82	0.89	1.03	0.98	0.85	0.90	0.66	0.82
$\rho1 = 0$	(-1.13)	(-3.19)	(-3.94)	(-0.55)	(1.41)	(2.85)	(4.23)	(4.13)	(3.42)	(3.45)	(2.53)	(2.41)	(2.79)	(3.57)
$\rho1 = 1$	(-1.72)	(-4.75)	(-8.95)	(-5.24)	(-2.98)	(-1.53)	(-0.92)	(-0.52)	(0.11)	(-0.08)	(-0.44)	(-0.26)	(-1.42)	(-0.80)
$\rho1(VRP^{DM})$	1.14	1.25	1.66	1.93	1.92	2.15	2.79	1.05	0.15	0.29	-0.92	-1.47	-3.95	1.27
$\rho2 = 0$	(3.81)	(2.26)	(4.16)	(6.00)	(4.98)	(4.32)	(3.34)	(0.98)	(0.14)	(0.28)	(-1.03)	(-1.32)	(-0.90)	(1.42)
$\rho2 = 1$	(0.46)	(0.45)	(1.65)	(2.89)	(2.39)	(2.31)	(2.14)	(0.04)	(-0.82)	(-0.70)	(-2.14)	(-2.22)	(-1.12)	(0.30)
R^2	3.1%	3.8%	5.3%	6.9%	6.9%	8.2%	7.9%	5.4%	5.9%	6.1%	5.8%	5.4%	7.8%	20.4%

Panel C: Net Capital Inflow Predictability

h	1	2	3	4	5	6	7	8
Predictors: Global VRP, Local Stock Returns, and Currency Returns								
$\rho(VRP^{Global})$	0.24	0.76	1.14	-1.11	-2.24	-2.47	-1.50	-1.39
$\rho = 0$	(0.47)	(2.06)	(3.11)	(-2.72)	(-5.10)	(-2.84)	(-2.33)	(-2.32)
$\rho = 1$	(-1.48)	(-0.65)	(0.38)	(-5.18)	(-7.37)	(-3.99)	(-3.88)	(-3.99)
R^2	0.3%	4.1%	4.8%	4.4%	11.3%	14.1%	10.5%	7.5%
Predictors: EM, DM VRPs, Local Stock Returns, and Currency Returns								
$\rho1(VRP^{EM})$	-0.21	-4.73	0.92	1.07	1.63	0.70	-0.47	0.94
$\rho1 = 0$	(-0.35)	(-6.00)	(3.63)	(2.17)	(2.02)	(0.48)	(-0.43)	(0.72)
$\rho1 = 1$	(-1.96)	(-7.26)	(-0.31)	(0.15)	(0.78)	(-0.21)	(-1.35)	(-0.05)
$\rho1(VRP^{DM})$	0.28	5.40	-1.09	-0.91	-2.97	-2.63	-1.26	-1.11
$\rho2 = 0$	(0.44)	(6.47)	(-0.72)	(-2.25)	(-5.44)	(-2.52)	(-2.03)	(-1.91)
$\rho2 = 1$	(-1.12)	(5.27)	(-1.39)	(-4.73)	(-7.27)	(-3.47)	(-3.64)	(-3.62)
R^2	1.4%	25.8%	9.1%	13.4%	20.5%	15.9%	9.5%	8.4%

Table F2: The Predictability of VRPs Period by Period in Emerging Markets

Panel A: Stock Market Return Predictability Month by Month

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	1.12	0.21	0.13	0.25	0.06	-0.01	-0.06	-0.03	-0.04	-0.01	0.00	0.01	-0.01	0.00
	(6.16)	(2.58)	(2.96)	(7.18)	(2.23)	(-0.36)	(-2.30)	(-1.57)	(-2.12)	(-0.79)	(-0.41)	(1.21)	(-1.07)	(0.46)
R^2	4.3%	0.6%	0.6%	3.5%	0.3%	0.0%	0.6%	0.2%	0.4%	0.0%	0.0%	0.1%	0.0%	0.0%
VRP^{EM}	0.16	0.13	0.05	0.13	0.13	0.12	0.07	0.03	0.03	0.03	0.01	0.00	-0.01	0.00
	(1.61)	(2.00)	(1.06)	(5.26)	(6.55)	(6.30)	(5.17)	(2.65)	(3.21)	(2.96)	(1.08)	(-0.25)	(-2.15)	(-1.63)
VRP^{DM}	1.00	0.11	0.10	0.15	-0.05	-0.10	-0.11	-0.05	-0.06	-0.03	-0.01	0.01	0.00	0.00
	(6.23)	(1.80)	(2.22)	(4.74)	(-1.87)	(-3.86)	(-4.17)	(-2.75)	(-3.75)	(-2.60)	(-0.80)	(1.08)	(0.04)	(0.73)
R^2	4.5%	0.8%	0.6%	4.5%	3.0%	3.6%	2.8%	0.7%	1.2%	0.8%	0.1%	0.1%	0.2%	0.1%

Panel B: Currency Return Predictability Month by Month

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.42	0.02	0.06	0.15	0.04	0.01	0.00	-0.01	0.00	0.01	0.00	0.00	0.00	0.00
	(4.05)	(0.45)	(2.34)	(7.58)	(3.74)	(0.80)	(-0.38)	(-1.83)	(0.30)	(1.45)	(-0.96)	(0.29)	(0.38)	(0.62)
R^2	3.6%	0.4%	1.0%	5.5%	0.6%	0.3%	0.9%	0.7%	0.3%	0.3%	0.1%	0.2%	0.2%	0.1%
VRP^{EM}	-0.06	-0.02	-0.03	0.04	0.05	0.03	0.02	0.00	0.01	0.02	0.00	0.00	0.00	0.00
	(-1.18)	(-0.43)	(-1.77)	(3.56)	(4.19)	(3.90)	(2.93)	(0.83)	(1.96)	(4.01)	(0.63)	(0.83)	(-1.85)	(-0.78)
VRP^{DM}	0.48	0.03	0.09	0.12	0.00	-0.02	-0.02	-0.02	0.00	-0.01	-0.01	0.00	0.00	0.00
	(5.58)	(0.80)	(3.09)	(6.92)	(0.22)	(-1.60)	(-1.98)	(-2.38)	(-0.72)	(-1.67)	(-1.08)	(-0.23)	(1.33)	(0.68)
R^2	4.3%	0.5%	1.7%	5.7%	2.0%	1.5%	1.7%	0.8%	0.4%	1.3%	0.1%	0.2%	0.4%	0.1%

Note: The table provides the panel regressions of stock market index returns in local currency, currency returns with respect to the U.S. dollar, and net capital inflows (not cumulative) on different VRPs in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors include the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance. Panel A reports the result for predicting h-month ahead stock market returns month by month, and Panel B shows the result for predicting h-month ahead currency returns month by month after controlling for both local and U.S. stock returns. Panel C reports the result for predicting h-quarter ahead net capital inflows quarter by quarter after controlling for local stock and currency returns. The VRPs are in monthly percentage-squared unit in Panels A and B, and in monthly percentage unit in Panel C. It provides the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period for stock and currency returns in Panels A and B is from January 2000 to October 2017. The sample period for capital inflows in Panel C is from Quarter 1, 2000 to Quarter 2, 2012.

Table F2: The Predictability of VRPs Period by Period in Emerging Markets—Continued

Panel C: Net Capital Inflow Predictability Quarter by Quarter

h	1	2	3	4	5	6	7	8
VRP^{Global}	3.51	4.41	1.46	-0.32	-0.55	-0.30	-0.99	-0.70
	(2.16)	(3.93)	(1.67)	(-0.35)	(-0.75)	(-0.44)	(-1.04)	(-0.81)
R^2	10.0%	6.2%	0.8%	1.1%	0.1%	0.2%	0.2%	0.6%
VRP^{EM}	-2.77	5.79	8.00	3.90	0.90	-0.74	-0.23	-0.05
	(-1.73)	(3.03)	(3.68)	(2.45)	(0.60)	(-0.54)	(-0.21)	(-0.04)
VRP^{DM}	5.30	0.18	-4.34	-3.15	-1.23	0.26	-0.72	-0.58
	(2.26)	(0.15)	(-2.42)	(-1.93)	(-0.90)	(0.22)	(-0.62)	(-0.51)
R^2	11.1%	8.9%	7.2%	2.8%	0.3%	0.2%	0.2%	0.5%

Table F3: The Predictability of log VRPs in Emerging Markets

Panel A: Stock Market Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.59	0.42	0.32	0.29	0.22	0.16	0.11	0.05	0.01	0.00	-0.01	-0.01	-0.05	0.02
	(6.21)	(5.29)	(4.47)	(4.12)	(3.36)	(2.66)	(1.86)	(0.88)	(0.19)	(0.00)	(-0.23)	(-0.16)	(-0.92)	(0.37)
R^2	2.8%	2.6%	2.2%	2.1%	1.5%	0.9%	0.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%
VRP^{EM}	0.42	0.46	0.53	0.53	0.52	0.55	0.58	0.58	0.59	0.59	0.55	0.53	0.35	0.29
	(3.15)	(3.78)	(4.41)	(4.51)	(4.63)	(4.94)	(5.33)	(5.24)	(5.51)	(5.70)	(5.52)	(5.52)	(5.02)	(4.09)
VRP^{DM}	0.38	0.20	0.09	0.05	-0.01	-0.07	-0.13	-0.18	-0.22	-0.24	-0.23	-0.22	-0.19	-0.11
	(3.95)	(2.45)	(1.15)	(0.75)	(-0.09)	(-1.03)	(-2.02)	(-2.81)	(-3.34)	(-3.47)	(-3.37)	(-3.24)	(-3.00)	(-1.58)
R^2	3.1%	3.5%	4.2%	4.8%	4.6%	4.9%	5.7%	6.0%	6.9%	7.5%	6.9%	6.7%	4.4%	3.0%

Panel B: Currency Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.25	0.19	0.14	0.16	0.14	0.13	0.13	0.10	0.09	0.08	0.07	0.06	0.05	0.06
	(5.29)	(4.79)	(4.53)	(5.37)	(4.99)	(5.13)	(5.16)	(4.05)	(3.80)	(3.76)	(3.20)	(2.93)	(2.69)	(3.10)
R^2	2.8%	3.2%	3.3%	4.3%	4.1%	4.3%	4.6%	2.9%	2.7%	2.9%	2.5%	2.5%	3.2%	4.5%
VRP^{EM}	-0.03	0.02	0.04	0.09	0.10	0.10	0.11	0.10	0.11	0.12	0.11	0.11	0.09	0.08
	(-0.49)	(0.42)	(0.83)	(2.01)	(2.26)	(2.46)	(2.73)	(2.39)	(2.80)	(3.45)	(3.46)	(3.51)	(3.88)	(3.88)
VRP^{DM}	0.24	0.17	0.12	0.12	0.10	0.09	0.08	0.06	0.04	0.03	0.02	0.02	0.02	0.02
	(5.54)	(4.57)	(4.17)	(4.40)	(3.95)	(3.97)	(3.80)	(2.60)	(2.02)	(1.51)	(1.10)	(0.86)	(0.74)	(1.15)
R^2	3.0%	3.4%	3.4%	4.7%	4.6%	4.9%	5.5%	3.6%	3.9%	4.6%	4.1%	4.0%	4.6%	5.6%

Note: The table provides the panel regressions of stock market returns in local currency, currency returns with respect to the U.S. dollar, and net capital inflows on different log VRPs in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are the value weighted emerging market (EM), developed market (DM) and global log VRPs. The log VRP is defined as the difference between the natural logarithm of implied variance and the natural logarithm of expected realized variance. Panel A reports the result for predicting h-month ahead cumulative stock market returns in annualized percentage unit. Panel B reports the result for predicting h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit after controlling for both local and U.S. stock market returns. Panel C shows the result for predicting h-quarter ahead total net capital inflows (percent of GDP) after controlling for quarterly local stock market returns and currency returns in percentage. The VRPs are in monthly percentage-squared unit in Panels A and B, and in monthly percentage unit in Panel C. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period for stock and currency returns in Panels A and B is from January 2000 to October 2017. The sample period for capital inflows in Panel C is from Quarter 1, 2000 to Quarter 2, 2012.

Table F3: The Predictability of log VRPs in Emerging Markets—Continued

Panel C: Net Capital Inflow Predictability

h	1	2	3	4	5	6	7	8
VRP^{Global}	1.89	2.58	1.73	0.89	0.67	0.59	0.49	0.39
	(2.14)	(3.25)	(2.42)	(1.30)	(1.03)	(0.93)	(0.82)	(0.71)
R^2	8.8%	10.8%	7.0%	3.1%	2.3%	1.6%	1.5%	1.4%
VRP^{EM}	-1.07	2.72	4.82	4.75	3.80	3.33	2.87	2.39
	(-0.73)	(2.20)	(3.70)	(3.78)	(3.28)	(3.05)	(2.69)	(2.33)
VRP^{DM}	2.24	1.36	-0.29	-1.05	-0.91	-0.80	-0.68	-0.58
	(2.10)	(1.58)	(-0.38)	(-1.30)	(-1.10)	(-0.95)	(-0.85)	(-0.76)
R^2	9.1%	11.8%	11.1%	8.4%	6.3%	5.2%	4.6%	3.9%

Table F4: The Predictability of Equally Weighted VRPs in Emerging Markets

Panel A: Stock Market Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.84	0.61	0.54	0.64	0.66	0.64	0.56	0.52	0.47	0.45	0.42	0.39	0.21	0.22
	(4.32)	(3.90)	(4.11)	(5.99)	(7.57)	(7.63)	(7.46)	(7.21)	(6.71)	(6.02)	(5.92)	(5.94)	(3.99)	(4.12)
R^2	3.2%	3.1%	3.4%	6.0%	7.6%	8.2%	7.0%	6.4%	5.8%	5.7%	5.2%	4.8%	1.8%	2.4%
VRP^{EM}	-0.07	0.00	0.05	0.12	0.20	0.29	0.31	0.32	0.31	0.31	0.29	0.28	0.16	0.14
	(-0.92)	(0.00)	(0.60)	(1.69)	(3.45)	(5.30)	(5.67)	(6.11)	(6.88)	(6.81)	(6.34)	(6.08)	(4.70)	(3.85)
VRP^{DM}	1.29	0.84	0.65	0.66	0.54	0.35	0.21	0.12	0.08	0.05	0.04	0.03	-0.02	0.05
	(7.29)	(6.82)	(6.70)	(7.35)	(6.62)	(4.88)	(2.97)	(1.58)	(1.02)	(0.60)	(0.53)	(0.43)	(-0.25)	(0.76)
R^2	5.6%	4.7%	4.6%	7.1%	8.1%	8.2%	7.2%	7.0%	6.5%	6.6%	6.1%	5.7%	2.4%	2.6%

Panel B: Currency Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.27	0.16	0.13	0.21	0.23	0.22	0.19	0.16	0.15	0.15	0.13	0.12	0.09	0.09
	(2.89)	(1.94)	(2.11)	(4.15)	(5.04)	(5.38)	(5.17)	(4.90)	(5.01)	(5.12)	(5.17)	(5.18)	(4.60)	(5.47)
R^2	2.5%	2.2%	2.5%	5.0%	6.5%	6.9%	6.2%	5.0%	5.0%	5.3%	5.0%	5.1%	4.9%	6.8%
VRP^{EM}	-0.09	-0.09	-0.09	-0.06	-0.02	0.02	0.03	0.04	0.04	0.04	0.04	0.04	0.03	0.03
	(-1.76)	(-1.97)	(-2.18)	(-1.71)	(-0.51)	(0.78)	(1.17)	(1.44)	(1.43)	(1.73)	(1.83)	(1.92)	(1.83)	(2.06)
VRP^{DM}	0.55	0.39	0.35	0.40	0.34	0.26	0.20	0.15	0.14	0.12	0.11	0.09	0.06	0.07
	(5.65)	(5.75)	(6.27)	(7.40)	(7.43)	(6.04)	(4.85)	(3.83)	(3.86)	(3.55)	(3.14)	(2.84)	(2.23)	(2.59)
R^2	4.9%	4.9%	5.9%	9.5%	9.9%	8.5%	7.1%	5.5%	5.4%	5.6%	5.2%	5.2%	4.9%	6.9%

Note: The table provides the panel regressions of stock market returns, currency returns, and net capital inflows on equally weighted VRPs in 9 emerging markets, which are Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, and Taiwan. Predictors are the equally weighted emerging market (EM), developed market (DM) and global VRPs. The VRP is defined as the difference between the implied variance and the conditional expectation of future realized variance. Panel A reports the result for predicting h-month ahead cumulative stock market returns in annualized percentage unit. Panel B reports the result for predicting h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit after controlling for both local and U.S. stock market returns. Panel C shows the result for predicting h-quarter ahead cumulative total net capital inflows (percent of GDP) after controlling for quarterly local stock market and currency returns in percentage. The VRPs are in monthly percentage-squared unit in Panels A and B, and in monthly percentage unit in Panel C. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period for stock and currency returns in Panels A and B is from January 2000 to October 2017. The sample period for capital inflows in Panel C is from Quarter 1, 2000 to Quarter 2, 2012.

Table F4: The Predictability of Equally Weighted VRPs in Emerging Markets—Continued

Panel C: Net Capital Inflow Predictability

h	1	2	3	4	5	6	7	8
VRP^{Global}	3.61	3.79	2.95	2.42	1.83	1.50	1.23	0.97
	(2.25)	(3.39)	(3.89)	(3.76)	(3.43)	(3.23)	(2.95)	(2.53)
R^2	10.4%	11.9%	8.7%	5.7%	4.1%	3.0%	2.6%	2.2%
VRP^{EM}	-1.39	1.87	3.30	3.67	3.35	2.79	2.57	2.21
	(-0.78)	(1.48)	(2.58)	(3.03)	(2.88)	(2.49)	(2.48)	(2.36)
VRP^{DM}	3.92	1.98	0.37	-0.30	-0.59	-0.52	-0.61	-0.59
	(1.87)	(1.55)	(0.39)	(-0.33)	(-0.70)	(-0.64)	(-0.85)	(-0.93)
R^2	11.3%	11.9%	9.5%	7.5%	6.1%	4.7%	4.4%	3.8%

Table F5: Stock Return Predictability in All MSCI Emerging and Developed Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
Panel A: Global VRP														
VRP^{Global}	0.95	0.62	0.53	0.59	0.57	0.49	0.38	0.34	0.29	0.25	0.22	0.23	0.16	0.20
	(12.85)	(10.89)	(11.89)	(15.75)	(17.38)	(15.86)	(13.78)	(12.42)	(10.44)	(9.42)	(8.56)	(8.82)	(7.19)	(7.93)
R^2	3.9%	3.1%	3.3%	5.4%	6.0%	5.0%	3.5%	3.1%	2.5%	2.0%	1.7%	1.9%	1.2%	2.2%
Panel B: EM and DM VRPs														
VRP^{EM}	0.11	0.14	0.14	0.18	0.26	0.32	0.33	0.33	0.33	0.33	0.31	0.28	0.18	0.16
	(2.49)	(3.62)	(3.55)	(5.43)	(9.10)	(11.79)	(12.35)	(12.42)	(13.30)	(13.75)	(13.43)	(12.81)	(10.37)	(9.39)
VRP^{DM}	0.87	0.50	0.42	0.45	0.37	0.24	0.13	0.10	0.05	0.01	-0.01	0.02	0.02	0.07
	(13.26)	(10.37)	(11.39)	(14.22)	(12.90)	(9.49)	(5.30)	(3.83)	(1.69)	(0.20)	(-0.24)	(0.60)	(0.76)	(2.60)
R^2	4.2%	3.3%	3.5%	5.8%	7.1%	7.5%	7.0%	6.9%	7.1%	7.1%	6.5%	6.0%	3.3%	3.6%

Note: This table provides the panel regression of h-month ahead cumulative stock returns in annualized percentage unit on VRPs in all MSCI developed and emerging markets. Predictors include the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage-squared unit. Additional to 9 emerging markets and 11 developed markets with available implied variance data in our sample, we include 14 emerging markets, which are Chile, Colombia, Peru, Czech Republic, Egypt, Greece, Hungary, Qatar, Turkey, United Arab Emirates, Indonesia, Malaysia, Philippines, Thailand, and 12 developed markets, which are Austria, Denmark, Finland, Ireland, Israel, Italy, Norway, Portugal, Spain, Sweden, New Zealand, Singapore. The market indices for the other MSCI emerging and developed markets are MSCI country indices. There are a total of 23 emerging markets and 23 developed markets. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from January 2000 to October 2017.

Table F6: Currency Return Predictability of VRPs in International Markets

Panel A: 9 Emerging Markets and 7 Developed Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.42	0.21	0.18	0.26	0.25	0.23	0.19	0.17	0.15	0.14	0.13	0.12	0.09	0.10
	(5.99)	(3.94)	(4.53)	(7.20)	(7.72)	(7.97)	(7.61)	(6.81)	(6.80)	(6.82)	(6.34)	(6.06)	(5.42)	(6.58)
R^2	3.9%	2.4%	2.7%	5.5%	6.0%	6.0%	5.2%	4.2%	4.2%	4.3%	4.0%	4.0%	4.0%	6.5%
VRP^{EM}	-0.03	-0.02	-0.04	0.00	0.04	0.06	0.07	0.07	0.06	0.07	0.06	0.06	0.03	0.04
	(-0.72)	(-0.71)	(-1.43)	(0.10)	(1.53)	(2.68)	(3.08)	(2.84)	(2.96)	(3.51)	(3.35)	(3.24)	(2.41)	(3.59)
VRP^{DM}	0.45	0.23	0.22	0.26	0.22	0.18	0.13	0.11	0.10	0.08	0.08	0.07	0.06	0.07
	(7.38)	(4.82)	(5.72)	(7.73)	(7.85)	(7.08)	(5.54)	(4.57)	(4.22)	(3.74)	(3.38)	(3.16)	(3.22)	(3.86)
R^2	4.4%	2.8%	3.4%	5.9%	6.1%	6.2%	5.6%	4.6%	4.6%	5.0%	4.6%	4.6%	4.0%	6.6%

Panel B: All MSCI Emerging and Developed Markets

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.42	0.21	0.18	0.25	0.23	0.21	0.19	0.16	0.15	0.14	0.12	0.11	0.08	0.09
	(9.65)	(6.03)	(7.10)	(10.96)	(11.68)	(11.77)	(11.48)	(10.32)	(10.24)	(10.05)	(9.28)	(8.74)	(7.45)	(8.90)
R^2	3.8%	2.1%	2.5%	5.1%	5.5%	5.4%	5.0%	4.1%	4.2%	4.2%	3.7%	3.7%	3.5%	5.4%
VRP^{EM}	0.00	-0.01	-0.03	0.02	0.05	0.07	0.08	0.07	0.07	0.08	0.07	0.06	0.03	0.04
	(-0.10)	(-0.47)	(-1.42)	(1.05)	(3.24)	(5.16)	(5.78)	(5.23)	(5.31)	(6.18)	(5.78)	(5.55)	(4.05)	(5.40)
VRP^{DM}	0.42	0.22	0.20	0.23	0.20	0.15	0.12	0.10	0.09	0.07	0.06	0.06	0.05	0.05
	(10.82)	(7.21)	(8.71)	(11.12)	(10.88)	(9.60)	(7.70)	(6.34)	(5.80)	(4.88)	(4.34)	(3.98)	(4.01)	(4.79)
R^2	4.2%	2.3%	2.9%	5.3%	5.6%	5.8%	5.7%	4.8%	4.9%	5.2%	4.7%	4.5%	3.8%	5.8%

Note: The table provides the panel regressions of h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit on different VRPs after controlling for local and U.S. stock returns in different international samples. Predictors are the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage-squared unit. Panel A reports the result in 9 emerging markets and 7 developed markets, which Brazil, China, India, Korea, Mexico, Poland, Russia, South Africa, Taiwan, Australia, Canada, HK, Japan, the Netherlands, Switzerland, and the U.K.. The U.S. is in dollar. Belgium, France, Germany, and the Netherlands are in Euro. Panel B reports the result in all MSCI emerging and developed markets. In Panel C, it reports the result after dropping China and HK from 9 emerging markets and 7 developed markets. In Panel D, the sample is based on all MSCI emerging and developed markets after dropping China, HK, Egypt, Qatar, and United Arab Emirates. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from January 2000 to October 2017.

Table F6: Currency Return Predictability of VRPs in International Markets—Continued

Panel C: 8 Emerging Markets and 6 Developed Markets without China and HK

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.48	0.24	0.21	0.30	0.28	0.26	0.22	0.19	0.17	0.17	0.15	0.14	0.10	0.12
	(6.11)	(3.95)	(4.56)	(7.52)	(8.30)	(8.75)	(8.21)	(7.34)	(7.31)	(7.37)	(6.80)	(6.46)	(5.69)	(6.98)
R^2	4.5%	2.9%	3.2%	6.5%	6.9%	7.0%	6.1%	5.0%	4.9%	5.1%	4.7%	4.7%	4.7%	7.6%
VRP^{EM}	-0.03	-0.02	-0.04	0.01	0.04	0.08	0.09	0.08	0.08	0.08	0.07	0.07	0.04	0.05
	(-0.65)	(-0.60)	(-1.32)	(0.24)	(1.69)	(2.93)	(3.37)	(3.13)	(3.27)	(3.90)	(3.74)	(3.65)	(2.75)	(4.08)
VRP^{DM}	0.51	0.26	0.25	0.29	0.25	0.20	0.15	0.12	0.11	0.09	0.08	0.08	0.07	0.08
	(7.62)	(4.78)	(5.75)	(8.07)	(8.20)	(7.25)	(5.50)	(4.53)	(4.17)	(3.69)	(3.33)	(3.12)	(3.19)	(3.88)
R^2	5.1%	3.2%	3.9%	6.8%	7.1%	7.2%	6.6%	5.4%	5.5%	6.0%	5.5%	5.4%	4.8%	7.8%

Panel D: All MSCI Emerging and Developed Markets without China, HK, Egypt, Qatar, and United Arab Emirates

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
VRP^{Global}	0.49	0.24	0.21	0.29	0.27	0.25	0.22	0.19	0.17	0.16	0.14	0.13	0.09	0.10
	(10.07)	(6.18)	(7.34)	(11.74)	(12.96)	(13.26)	(12.68)	(11.37)	(11.23)	(11.05)	(10.06)	(9.42)	(8.11)	(9.67)
R^2	4.9%	2.7%	3.2%	6.3%	6.8%	6.7%	6.2%	5.1%	5.2%	5.2%	4.7%	4.6%	4.4%	6.7%
VRP^{EM}	0.00	-0.01	-0.03	0.02	0.05	0.08	0.09	0.08	0.08	0.09	0.08	0.07	0.04	0.04
	(-0.17)	(-0.52)	(-1.45)	(1.06)	(3.30)	(5.36)	(6.09)	(5.55)	(5.68)	(6.63)	(6.24)	(6.04)	(4.56)	(6.36)
VRP^{DM}	0.50	0.25	0.24	0.27	0.23	0.18	0.14	0.12	0.10	0.08	0.07	0.07	0.06	0.06
	(11.63)	(7.48)	(9.24)	(12.19)	(11.97)	(10.39)	(8.10)	(6.62)	(6.06)	(5.14)	(4.53)	(4.16)	(4.27)	(5.03)
R^2	5.3%	2.9%	3.7%	6.6%	6.9%	7.2%	7.0%	5.9%	6.0%	6.4%	5.7%	5.6%	4.7%	7.1%

Table F7: Net Capital Inflow Predictability of VRPs in International Markets

Panel A: 9 Emerging Markets and 10 Developed Markets

h	1	2	3	4	5	6	7	8
VRP^{Global}	1.99	2.09	2.05	1.87	1.58	1.17	0.66	0.45
	(1.71)	(1.93)	(2.36)	(2.47)	(2.17)	(1.82)	(1.08)	(0.81)
R^2	2.4%	2.5%	2.1%	1.5%	1.1%	0.6%	0.2%	0.2%
VRP^{EM}	-0.58	0.92	1.59	1.75	1.72	1.46	1.22	0.90
	(-0.40)	(0.87)	(1.47)	(1.55)	(1.55)	(1.41)	(1.37)	(1.16)
VRP^{DM}	2.33	1.34	0.81	0.52	0.26	0.07	-0.24	-0.19
	(1.34)	(0.96)	(0.84)	(0.58)	(0.32)	(0.09)	(-0.28)	(-0.27)
R^2	2.5%	2.5%	2.4%	1.8%	1.6%	1.0%	0.6%	0.4%

Panel B: All MSCI Emerging and Developed Markets

h	1	2	3	4	5	6	7	8
VRP^{Global}	-0.39	0.30	0.51	0.41	0.37	0.30	0.10	-0.04
	(-0.42)	(0.39)	(0.83)	(0.77)	(0.77)	(0.69)	(0.25)	(-0.12)
R^2	1.1%	1.1%	1.1%	0.8%	0.8%	0.6%	0.6%	0.5%
VRP^{EM}	-0.57	0.49	1.24	1.47	1.61	1.73	1.75	1.50
	(-0.51)	(0.53)	(1.44)	(1.83)	(2.15)	(2.53)	(2.86)	(2.71)
VRP^{DM}	0.13	0.02	-0.33	-0.61	-0.77	-0.92	-1.13	-1.09
	(0.11)	(0.02)	(-0.46)	(-0.99)	(-1.37)	(-1.69)	(-2.13)	(-2.36)
R^2	1.1%	1.1%	1.3%	1.2%	1.3%	1.3%	1.4%	1.1%

Note: This table provides the result for the panel regressions of h-quarter ($h = 1, 2, ..., 8$) ahead cumulative total net capital inflows (percent of GDP) on VRPs after controlling for local stock market returns and currency returns in international markets. Predictors are the value weighted emerging market (EM), developed market (DM), and global VRPs. The VRP is calculated as the difference between the implied variance and the conditional expectation of future realized variance in monthly percentage unit. Net capital inflows are the difference between gross inflows and gross outflows. Panel A includes the sample of 9 emerging markets and 10 developed markets. There is no capital inflow data for HK. Panel B includes the sample of all MSCI emerging and developed markets. The capital flow data are not available in Qatar and United Arab Emirates. It provides the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period is from Quarter 1, 2000 to Quarter 2, 2012.

Table F8: The Predictability of Regional VRPs in all MSCI Markets

Panel A: Stock Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
$VRP^{Regional}$	-0.08	-0.04	-0.04	-0.02	0.03	0.08	0.08	0.09	0.10	0.11	0.10	0.08	0.06	0.04
	(-3.20)	(-1.95)	(-2.22)	(-1.13)	(2.31)	(5.12)	(5.72)	(6.66)	(7.66)	(8.53)	(7.99)	(7.29)	(6.15)	(4.30)
VRP^{Global}	1.02	0.66	0.57	0.61	0.54	0.42	0.30	0.26	0.19	0.15	0.13	0.15	0.10	0.17
	(14.07)	(11.97)	(13.38)	(15.94)	(15.82)	(13.81)	(11.01)	(9.19)	(6.67)	(5.56)	(4.81)	(5.49)	(4.42)	(5.98)
R^2	4.1%	3.2%	3.5%	5.4%	6.1%	5.7%	4.4%	4.3%	4.2%	4.0%	3.5%	3.3%	2.1%	2.7%

Panel B: Currency Return Predictability

h	1	2	3	4	5	6	7	8	9	10	11	12	18	24
$VRP^{Regional}$	0.02	-0.01	-0.02	-0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.01	0.01
	(1.17)	(-0.57)	(-1.67)	(-0.63)	(1.06)	(3.29)	(3.71)	(4.20)	(4.15)	(4.48)	(4.60)	(4.54)	(1.53)	(2.11)
VRP^{Global}	0.45	0.22	0.21	0.27	0.23	0.20	0.17	0.14	0.13	0.11	0.10	0.09	0.07	0.09
	(10.35)	(6.55)	(7.77)	(11.08)	(11.12)	(10.73)	(9.98)	(8.51)	(8.42)	(7.80)	(6.80)	(6.19)	(6.00)	(7.41)
R^2	4.7%	2.2%	2.7%	5.5%	5.8%	6.1%	5.7%	4.8%	5.0%	4.9%	4.5%	4.3%	3.5%	6.0%

Panel C: Net Capital Inflow Predictability

h	1	2	3	4	5	6	7	8
$VRP^{Regional}$	0.19	-0.01	0.36	0.31	0.32	0.54	0.46	0.62
	(0.18)	(-0.01)	(0.35)	(0.31)	(0.37)	(0.64)	(0.60)	(0.84)
VRP^{Global}	-0.52	0.31	0.19	0.15	0.11	-0.15	-0.29	-0.58
	(-0.37)	(0.24)	(0.17)	(0.14)	(0.12)	(-0.18)	(-0.35)	(-0.76)
R^2	0.9%	1.0%	1.0%	0.7%	0.7%	0.6%	0.5%	0.4%

Note: The table provides the panel regressions of stock market returns, currency returns, and net capital inflows on regional VRPs and global VRPs in all MSCI emerging and developed markets. For each market, the VRP is the corresponding regional VRP. There are three regional VRPs. China, HK, India, Korea, Japan, Taiwan, et al. are corresponding to the aggregated Asia-pacific VRP. Brazil, Canada, Chile, Mexico, the U.S., et al. are corresponding to the aggregated Americas VRP. Belgium, Egypt, France, Germany, Italy, Russia, the U.K., et al. are corresponding to the aggregate Europe VRP. The VRP is defined as the difference between the implied variance and the conditional expectation of future realized variance. Panel A reports the result for predicting h-month ahead cumulative stock market returns in annualized percentage unit. Panel B reports the result for predicting h-month ahead cumulative currency returns with respect to the U.S. dollar in annualized percentage unit after controlling for both local and U.S. stock market returns. Panel C shows the result for predicting h-quarter ahead cumulative total net capital inflows (percent of GDP) after controlling for quarterly local stock market returns and currency returns in percentage. The VRPs are in monthly percentage-squared unit in Panels A and B, and in monthly percentage unit in Panel C. We report the coefficients, the Newey and West (1987) t statistics with h lags (reported in parentheses), and the R^2. The sample period for stock and currency returns in Panels A and B is from January 2000 to October 2017. The sample period for capital inflows in Panel C is from Quarter 1, 2000 to Quarter 2, 2012.