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# Variance risk premiums in emerging markets[☆]

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ABSTRACT

We provide for the first time the emerging market variance risk premium (EMVRP) from 2006 to 2023, based on nine emerging stock and option markets—Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan. The EMVRP significantly predicts international stock returns and currency appreciation rates, especially for horizons longer than six months. This is in sharp contrast with the predictive pattern of the developed market variance risk premium (DMVRP), which is more important over horizons shorter than six months. These findings are consistent with an illustrative model incorporating partial market integration and heterogeneous economic uncertainty.

## 1. Introduction

Economic uncertainty affects future consumption and investment decisions, and thus returns on different assets. Several recent studies, such as Drechsler and Yaron (2011) and Drechsler (2013) present evidence that economic uncertainty can be proxied by the variance risk premium (VRP). In these studies, the VRP is measured as the difference between the risk-neutral and physical expectations of future return variance. As a proxy for economic uncertainty, the VRP contains relevant information about the future investment opportunity set, and should predict returns on investments. Empirically, Bollerslev et al. (2009), Bollerslev et al. (2014), Londono (2015), and Londono and Xu (2023) show that the VRP can predict stock returns. Londono and Zhou (2017) show that the VRP can predict currency returns, among others.

Most of these studies construct the VRP using the U.S. data, such as Bollerslev et al. (2009), or data from developed countries, such as Bollerslev et al. (2014) and Londono (2015). However, the VRP from emerging markets (EMVRP hereafter) has never been considered. Globalization has been marked by rapid and dramatic economic growth and market capitalization growth in emerging markets. As shown in Fig. 1, the economic activity from emerging markets, measured by GDP, reaches 30.92 trillion dollars by the end of 2023, accounting for more than 39% of the global GDP. Meanwhile, the market capitalization in emerging markets increases from 3.37 trillion dollars in 2006 to 14.12 trillion dollars by the end of 2023, accounting for 16.40% of the global capitalization. As a proxy for economic uncertainty rooting from these markets, it is interesting to understand the behavior and properties of EMVRP. Can the EMVRP predict important economic variables, such as stock market returns and currency returns? Does it provide more or differential information than the VRP constructed from developed markets? In this study, we fill the gap in the literature, and construct for the first time the EMVRP to examine its predictive power for stock and currency returns in the global capital market.

We construct the EMVRP from country-level (or market-level) variance risk premiums in nine major emerging markets – Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan – over the sample period from January 2006 to December 2023.

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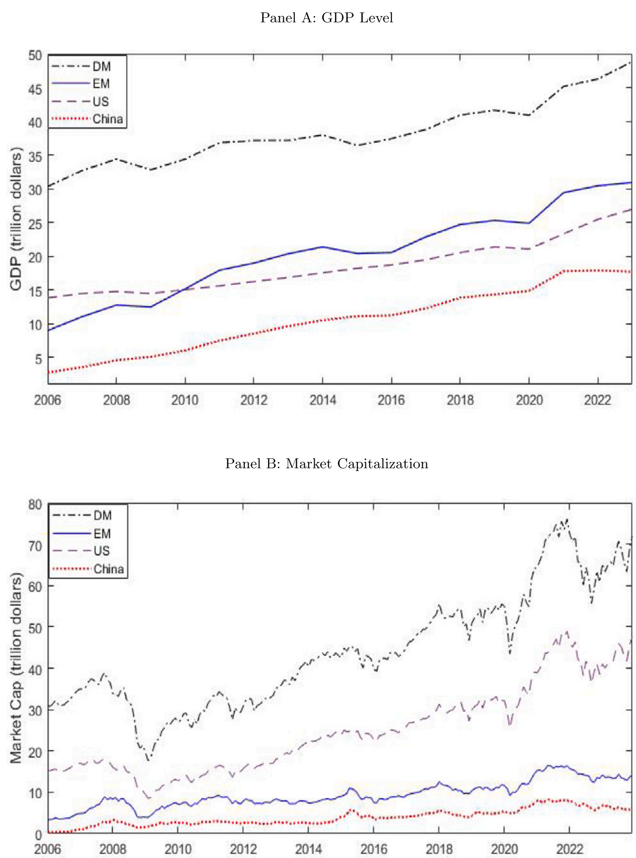


**Fig. 1.** GDP and Market capitalization.
This figure plots the annual current price GDP and monthly stock market capitalization in the U.S. dollar in developed markets (DM), emerging markets (EM), the U.S., and China from January 2006 to December 2023. The total market capitalization (GDP) in developed markets is the sum of market capitalization (GDP) from eleven developed markets: Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S. Similarly, the total market capitalization (GDP) in emerging markets is the sum of market capitalization (GDP) from nine emerging markets: Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan.

We first compute country-level VRPs as the difference between the option-implied variance and the expectation of future realized variance, where the model-free implied variance from option prices is calculated as in Carr and Madan (1998), Britten-Jones and Neuberger (2000), and Jiang and Tian (2005), and the realized variance is calculated as the sum of squared daily returns over one month, following the spirit of Andersen and Bollerslev (1998) and Andersen et al. (2003). We compute the EMVRP as the market capitalization weighted average of all emerging market country-level VRPs, which captures the commonality among the VRPs from individual emerging markets. The relatively long time series of EMVRP data is useful in many fields, especially in international finance and related areas. In parallel, we also construct a developed market VRP (DMVRP hereafter) as the market capitalization weighted average of eleven developed market country-level VRPs, including Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the United Kingdom (U.K.), and the United States (U.S.). Our summary statistics show that the EMVRP's correlation with the DMVRP is merely 0.11. The aggregation of country-level VRPs into the EMVRP and DMVRP allows us to compare the predictive power of the two, and shed light on their differential information content.

Can economic uncertainty affect stock returns? Bollerslev et al. (2009) find that the U.S. VRP can significantly predict stock returns in the U.S., while Bollerslev et al. (2014) show that the DMVRP can predict stock returns in developed economies. For our study, the interesting question becomes: does the EMVRP provide additional predictive power for future stock returns beyond that of the DMVRP? We use the EMVRP, together with the DMVRP, to predict returns on stock indices from the nine emerging markets, eleven developed markets, and 46 MSCI countries. Our empirical findings are three fold. First, the EMVRP, by itself, can significantly predict returns from all markets, especially for horizons longer than three months, with the adjusted $R^2$s ranging between 5.1% and 14.2%. Second, the DMVRP, as a proxy for world aggregate systematic risk or economic uncertainty, shows significant and stronger predictive power for stock returns over most of the shorter forecasting horizons. Finally, when we include both the EMVRP and DMVRP, the significance of EMVRP stays the same over longer horizons, while the DMVRP is significant for predicting stock market returns over shorter horizons. The inclusion of EMVRP increases the adjusted $R^2$s by an average of 5.0%, indicating that the EMVRP provides additional information than the DMVRP.

Forecasting currency returns is one of the most challenging empirical tasks in international macroeconomics. Meese and Rogoff (1983) and Rogoff (2009) show that macroeconomic fundamentals, which should drive exchange rate variation, are incapable of predicting exchange rate fluctuations. Londono and Zhou (2017) use the U.S. stock VRP to predict currency returns, and the $R^2$s are bumped up to 5.57% at the 1-month horizon. Here, does the EMVRP provide differential predictive power than that of the U.S. VRP or DMVRP? Our empirical results show that the EMVRP, by itself, can significantly predict nine emerging market currency returns for horizons longer than six months, with the adjusted $R^2$s ranging between 3.6% and 13.4%. Together with the DMVRP, these adjusted $R^2$s increase to 5.5%–14.7%. The DMVRP is more significant over shorter horizons, while the EMVRP is more important over longer horizons. These findings are quite similar to those for stock index returns. That is, the EMVRP contains significant predictive information for future stock and currency returns, and the information differs significantly from that contained in the DMVRP.

In addition to demonstrating the in-sample predictive power of EMVRP, we compare the out-of-sample predictive ability with that of the historical mean model, following Welch and Goyal (2008). We find that the predictive power of EMVRP is preserved, as evidenced by the consistently positive values of the out-of-sample $R^2$ statistics proposed by Campbell and Thompson (2008) and the low $p$-values associated with the test statistics introduced by Clark and West (2007) and Diebold and Mariano (2002) over long horizons. Specifically, we find that the out-of-sample $R^2$ statistics of EMVRP are higher than those of the DMVRP for horizons beyond three months. Moreover, these statistics are statistically significant, with $p$-values less than 5%.

What drives the differential predictive patterns of EMVRP and DMVRP? To answer this question, we propose a two-country consumption-based model with partial integration. We assume that the developed market is fully integrated into the global economy, while the emerging market is only partially integrated, which is consistent with the literature on market integration, such as Bekaert and Harvey (1995). Based on the real consumption data, we also assume that the emerging economy has higher consumption growth volatility. With closed-form solution and calibration results, we are able to match the differential predictive patterns of EMVRP and DMVRP for future asset returns. In a nutshell, since the consumption growth in emerging markets is more volatile, the VRP and the returns in emerging markets are more affected by the more persistent component of economic uncertainty than those in developed markets. The partial integration makes the EMVRP and emerging market returns load even more on the more persistent component of economic uncertainty. Implied by the model, the EMVRP, with higher persistence, dominates the return predictability over longer horizons. Although the model is quite stylized and illustrative in nature, it can rationalize our main empirical findings that the EMVRP and the DMVRP predict global stock returns over different horizons.

Our novel empirical findings contribute to the literature in three ways. First, while the short-run return predictive patterns of DMVRP have been documented in major developed stock markets (Bollerslev et al., 2009; Bollerslev et al., 2014; and Londono, 2015, among others), our study further extends the scope and examines the return predictability with the EMVRP.[1] We document a novel empirical finding that the EMVRP has strong predictive power for stock and currency returns over longer horizons. Given that the DMVRP has strong predictive power for stock returns over shorter horizons, our finding indicates that the EMVRP contains differential and complementary information compared to the DMVRP, which may be interpreted as the global variance risk premium. The strong and different predictive power of EMVRP indicates that emerging markets potentially generate a different kind of risk premium, which is also important for all asset markets.

Second, we contribute to the literature on stock market return predictability. For instance, previous studies identify a few variables that have significant predictive power for future stock returns, such as the VRP by Bollerslev et al. (2009), the short rate by Rapach et al. (2016), the negative jump risk premium by Andersen et al. (2020), the implied volatility spread by Han and Li (2021), and the aggregate expected investment growth by Li et al. (2021). Motivated by these studies on stock market return prediction, our primary contribution lies in estimating the EMVRP and using it to predict global stock market returns through in-sample and out-of-sample tests.

Third, our work builds on a recent line of research that seeks to predict currency returns in time series. For instance, Londono and Zhou (2017) find that the world currency VRP and the U.S. stock VRP can predict currency returns within one year. Richmond (2019) shows that countries' trade network centrality is negatively related to currency risk premiums in the next month. Jiang et al. (2021) document that the convenience yield can predict dollar exchange rates. Andersen et al. (2021) find that the U.S. option-implied tail risk measure has significant forecast power for dollar–yen exchange rate returns over 1–12 months. Motivated by recent studies on predicting currency returns, we use both the EMVRP and DMVRP to predict currency returns and compare the predictive power of the two.

The remainder of this paper is organized as follows. In Section 2, we describe our methodology on how to construct VRPs and how to predict future returns. Section 3 introduces the data and provides summary statistics. Section 4 presents the main empirical results, and we use VRPs to predict stock market returns and currency returns for in-sample and out-of-sample tests. Section 5 conducts several robustness tests. Section 6 concludes.

## 2. Methodology

We define the variance risk premium variables in Section 2.1. The predictive regressions are specified in Section 2.2. In Section 2.3, we discuss out-of-sample tests.

### 2.1. Variance risk premium definition

We define the VRP as the difference between the expected variance under the risk-neutral measure and the expected variance under the physical measure. That is, for market $i$ in 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 option-implied variance, and $E_t(RV_{t+1}^i)$ is the expected variance under the physical measure. A typical choice for the risk-neutral variance is the option-implied variance. For instance, many researchers use the squared VIX, the implied variance of the market index options constructed by the Chicago Board Options Exchange (Cboe), as the implied variance for the U.S. stock index.

To compute the expected realized variance, we start with realized variance, which is generally computed by summing the daily squared index returns over $D$ trading days within month $t$, following the spirit of Andersen and Bollerslev (1998) and Andersen et al. (2003),

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

where $r_{i,d}$ denotes the daily return for market $i$ on day $d$, and day $d$ belongs to month $t$. To compute the expectation of realized variance, $E_t(RV_{t+1}^i)$, we follow Bekaert and Hoerova (2014) to project the logarithm of realized variance $\log(RV_t^i)$ on a set of predictors in month $t-1$,

$$\log(RV_t^i) = z_{t-1}^i\theta^i + \varepsilon_t^i. \tag{3}$$

Here the 1 by $J$ vector $z_{t-1}^i$ includes a constant and $J-1$ predictors at time $t-1$, and $\theta^i$ denotes the $J$ by 1 vector of parameters. Combining the predictors in Corsi (2009) and Bekaert and Hoerova (2014), we include the lagged natural logarithm of monthly realized variance, $\log(RV_{t-1}^i)$, the natural logarithm of weekly realized variance, $\log(RVW_{t-1}^i)$, the natural logarithm of daily realized variance, $\log(RVD_{t-1}^i)$, the downside monthly return, $Return21_{t-1}^i$, the downside weekly return, $Return5_{t-1}^i$, and the downside daily return, $Return1_{t-1}^i$, at time $t-1$ to account for persistence and asymmetry.[2] To avoid any forward-looking information to obtain $E_t(\log(RV_{t+1}^i))$, for each time $t$, we estimate $\theta_t^i$ and $E_t(\log(RV_{t+1}^i))$ using information from 0 to $t$. If the return sample starts before 1990, we start the estimation from 1990; otherwise, we start from the earliest available date in the sample. Finally, when considering a logarithmic model, we assume log-normality to predict levels of monthly realized variances, following Bekaert and Hoerova (2014):

$$E_t(RV_{t+1}^i) = \exp(E_t(\log(RV_{t+1}^i)) + 0.5var(\log(RV_{t+1}^i))). \tag{4}$$

We use the logarithmic model to compute the conditional expectation of $\log(RV_{t+1}^i)$ and the sample variance of $\log(RV_{t+1}^i)$ to compute the variance term.

After constructing country VRPs, we define the EMVRP and DMVRP as follows,

$$\begin{aligned} EMVRP_t &= \sum_{ei=1}^{n_1}(w_t^{ei}\times VRP_t^{ei}), \text{market } ei \in \text{emerging markets},\\ DMVRP_t &= \sum_{di=1}^{n_2}(w_t^{di}\times VRP_t^{di}), \text{market } di \in \text{developed markets}, \end{aligned} \tag{5}$$

[1] Bollerslev et al. (2014) and Londono (2015) focus on eight 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 in Londono and Zhou (2017), credit default spreads in Wang et al. (2013), and bond risk premiums in Mueller et al. (2019) and Grishchenko et al. (2022). Hattori et al. (2021) construct VRPs in India, Korea, and Mexico from 2007 to 2015. Their findings reveal significant spillovers from the U.S. and developed Eurozone's VRPs to the VRPs of other emerging economies, especially during the post-Global Financial Crisis period. They decompose the VRPs into the variance-diffusive risk premium and variance-jump risk premium, with the former driving the equity fund inflow from the U.S. to other major advanced economics.

[2] We consider the model described above as our benchmark model. We experiment two alternative models to enhance the estimation efficiency of $E_t(\log(RV_{t+1}^i))$. (1) We adopt the predictors from the HAR model similar to Corsi (2009), including the lagged natural logarithms of monthly, weekly, and daily realized variances. The adjusted $R^2$ is lower than that of the benchmark model. (2) Besides the six lagged predictors in the benchmark model, we include macro variables, such as the CPI growth rate, unemployment rate, economic policy uncertainty of Baker et al. (2016), and GDP growth rate. The estimation results show that adding macro variables does not significantly improve the adjusted $R^2$. Moreover, in most cases, the coefficients on macro variables are not statistically significant. Some macro variables have starting dates after 1990; hence, we use the benchmark model to estimate $E_t(\log(RV_{t+1}^i))$.

Here, the weight, $w_t$, is computed using the entire individual stock market capitalization in the U.S. dollar at time $t$. If there are commonalities or common risks in country-level VRPs, aggregating VRPs over the developed and emerging market levels would capture these common components.

### 2.2. Predictive regressions for stock and currency returns

Bollerslev et al. (2014) use the DMVRP to predict developed market stock index returns in panel regressions. We adopt a similar specification to examine the predictive power of country-level VRPs ($VRP^i$), EMVRP, and DMVRP for stock index returns as follows,

$$r^i_{t,t+h} = a_h + b_h VRP_t + CountryFE^i + \epsilon^i_{t,t+h}, \tag{6}$$

where the cumulative market return is computed as $r^i_{t,t+h} = (1/h)[(1+r^i_{t+1})(1+r^i_{t+2})...(1+r^i_{t+h})-1]$, $r^i_t$ denotes the stock excess return in month $t$ for market $i$. The variable $VRP_t$ can consist of one or a combination of $VRP^i$, EMVRP, and DMVRP in month $t$. We choose the horizons $h = 1, 3, 6, 9, 12, 18$, and 24 months. Here we add in country fixed effects, $CountryFE^i$, to capture potential differences in returns across countries. To compare different coefficients, we standardize the VRP variables so they all have zero means and unit standard deviations.

For the coefficients, we compute the standard errors with two-way clustering by market and month, following Thompson (2011), as our panel data contains observations on multiple markets across multiple time periods.[3] In this setup, if the VRPs can significantly predict future stock index returns, we expect the coefficients, $b_h$, to be significantly different from zero. Other than significance, we also investigate the explanatory power of VRP variables for future stock index returns using the adjusted $R^2$ statistics.

For currency returns, we estimate a similar specification as in Londono and Zhou (2017),

$$xr^i_{t,t+h} = a_h + b_h VRP_t + c_h(ir^{US}_t - ir^i_t) + CountryFE^i + \epsilon^i_{t,t+h}. \tag{7}$$

Here, the variable $xr^i_{t,t+h} = (1/h)[(1+xr^i_{t+1})(1+xr^i_{t+2})...(1+xr^i_{t+h})-1]$, $xr^i_t$ denotes the currency return with respect to the U.S. dollar for currency $i$ in month $t$, computed as

$$xr^i_t = (s^i_t - s^i_{t-1})/s^i_{t-1}, \tag{8}$$

where $s^i_t$ denotes the spot exchange rate with respect to the U.S. dollar (quoted in units of U.S. dollar per one unit of foreign currency) for currency $i$ in month $t$. As before, the variable $VRP_t$ can consist of one or a combination of $VRP^i$, EMVRP, and DMVRP in month $t$, and $h = 1, 3, 6, 9, 12, 18$, and 24 months. Based on uncovered interest rate parity, we include the interest rate differential between the U.S. and the foreign country $(ir^{US}_t - ir^i_t)$ as controls. The standard errors are computed with two-way clustering by market and month. If the VRPs can predict currency returns, we expect the coefficients, $b_h$, to be significantly different from zero.

### 2.3. Out-of-sample tests

As indicated in Welch and Goyal (2008), Rapach et al. (2016), Han and Li (2021), and Li et al. (2021), out-of-sample tests are important for assessing the validity of predictive regressions. For instance, Welch and Goyal (2008) find that numerous economic variables with in-sample predictive ability for the equity premium fail to deliver consistent out-of-sample forecasting gains relative to the historical average. To make sure that the predictive relations we document in this study are not artifacts of in-sample estimation, we design the following out-of-sample test to examine the robustness of our in-sample results, following Campbell and Thompson (2008) and Welch and Goyal (2008).

We first divide our sample into in-sample (January 2006 to December 2010) and out-of-sample (January 2011 to December 2023) portions.[4] We use stock return prediction as an example. For each market $i$'s cumulative stock return $r^i_{t,t+h}$ in the out-of-sample period, we employ the recursively expanding estimation scheme to compute the forecast $\hat{r}^i_{t,t+h}$ and $\bar{r}^i_{t,t+h}$ as

$$\begin{aligned} &Model\ \ Prediction: \quad \hat{r}^i_{t,t+h} = \hat{a}_{h,t} + \hat{b}_{h,t} VRP_t + \widehat{CountryFE}^i_t, \\ &Historical\ \ Mean: \quad \bar{r}^i_{t,t+h} = \frac{1}{t-h}\sum_{j=1}^{t-h} r^i_{j,j+h}, \end{aligned} \tag{9}$$

where $\hat{a}_{h,t}$, $\hat{b}_{h,t}$, and $\widehat{CountryFE}^i_t$ are the estimates of the parameters from a panel regression in Eq. (6) based on the data from the beginning of the sample through time $t$ during the out-of-sample period (January 2011 to December 2023), and $\bar{r}^i_{t,t+h}$ is the historical average excess return for market $i$. Using the historical mean as a benchmark forecast implies that $b_h$ in Eq. (6) is zero, indicating that returns are not predictable.

To compare the predictive accuracy of the in-sample model prediction and the historical mean benchmark, we next follow previous empirical work and quantify the forecast errors as:

$$\begin{aligned} e_{i,t+h,1} &= r^i_{t,t+h} - \bar{r}^i_{t,t+h}, \\ e_{i,t+h,2} &= r^i_{t,t+h} - \hat{r}^i_{t,t+h}. \end{aligned} \tag{10}$$

Next, we define the quadratic function of the forecast errors and the out-of-sample $R^2$ as,

$$\begin{aligned} MSFE_1 &= \frac{1}{nT}\sum_{i=1}^{n}\sum_{t+h=1}^{T} e^2_{i,t+h,1}, \\ MSFE_2 &= \frac{1}{nT}\sum_{i=1}^{n}\sum_{t+h=1}^{T} e^2_{i,t+h,2}, \\ OOSR^2 &= 1 - \frac{MSFE_2}{MSFE_1}, \end{aligned} \tag{11}$$

where $T$ is the number of monthly observations during the out-of-sample evaluation period. For currency returns, the forecast errors, $MSFE$, and out-of-sample $R^2$ can be defined in a similar fashion. If our in-sample estimation preforms well in the out of sample, better than the historical mean benchmark, we would have $MSFE_1 > MSFE_2$ or, alternatively, a positive out-of-sample $R^2$.

Our null hypothesis is that the historical mean forecast is not inferior to the VRP model forecast, against the alternative that the historical mean forecast is inferior to the VRP model forecast. To test this hypothesis, we consider two statistics, $J^{CW}_{n,T}$ and $J^{DM}_{n,T}$. Technical details for these two tests are provided in Internet Appendix A; here, we only discuss the intuition. Since our VRP model and the benchmark prevailing mean model are nested, we first follow Clark and West (2007) to conduct the population-level predictive test using $J^{CW}_{n,T}$. We calculate and provide the $p$-values associated with the test statistic

[3] Double-clustered standard errors adjust standard errors for correlation either across market or across time, which have less bias but higher estimation variance. For robustness checks, we also estimate the standard errors using the Newey and West (1987) method with $h$ lags to account for autocorrelation in the error terms. Unreported results confirm that our findings remain robust, showing higher $t$-statistics. Additionally, Stambaugh (1999) shows that the statistical inferences of coefficients in Eq. (6) have large finite-sample bias when predictor variables are persistent. To address this issue, we first follow Bollerslev et al. (2014) to predict stock returns with VRPs and report the Stambaugh (1999) bias, which is economically small for all VRP measures. In addition, we follow Li et al. (2021) to conduct Monte Carlo simulations for the predictive regressions and find that the sample size distortion is economically small for our main results.

[4] The literature is largely silent on the best way to split the sample into in-sample and out-of-sample portions. More in-sample observations imply more accurate forecasts, while more out-of-sample observations imply more information regarding the accuracy of forecasts. To maximize testing power, our out-of-sample portion is longer than our in-sample portion. Similar choices can be found in Welch and Goyal (2008) and Rapach et al. (2016).

**Table 1**
Data.
This table lists the option-implied volatility (IV) index and the corresponding underlying stock index in both emerging (Panel A) and developed markets (Panel B). It provides the name, starting date of the option-implied volatility index and the corresponding underlying stock index, as well as the data source of the option-implied volatility index. Note that for * markets, the Mexico VIMEX is no longer available after June 2017. The Poland VWIg20 is no longer available after June 2013. The Russia RSVX is no longer available after 9 December 2016; it becomes the RVI index. The Belgium VBEL is no longer available after November 2010. For Canada, the option-implied volatility index is the MVX from 2002 to 2009, the VIXC after 2009, and S&P/TSX 60 VIX index after January 2020. The France VCAC 40 and the Netherlands VAEX are not available after December 2020. The UK VFTSE is not available after June 2019; it becomes IVUKX30.

| Market | Stock index | Starting date | IV | Starting date | IV source |
|---|---|---|---|---|---|
| Panel A: Emerging markets | | | | | |
| Brazil | EWZ ETF | 200 007 | VXEWZ | 201 103 | DataStream |
| China | SSE 50 | 200 401 | CIVIX | 201 502 | Wind |
| India | Nifty 50 | 199 604 | INVIXN | 200 701 | Bloomberg |
| South Korea | KOSPI 200 | 199 001 | VKOSPI | 200 301 | Bloomberg |
| Mexico | Mexico IPC | 198 801 | VIMEX | 200403* | DataStream |
| Poland | Wig 20 | 199 406 | VWIg20 | 200309* | Volatility Trading |
| Russia | RTS | 199 509 | RTSVX/RVI* | 200 601 | DataStream/Bloomberg |
| South Africa | FTSE/JSE Top 40 | 199 507 | JSAVI | 200 702 | DataStream |
| Taiwan | TAIEX | 197 101 | TAIEX VIX | 200 612 | Taiwan Futures Exchange |
| Panel B: Developed markets | | | | | |
| Australia | S&P/ASX 200 | 199 205 | AXVI | 200 801 | DataStream |
| Belgium | BEL 20 | 199 001 | VBEL | 200001* | DataStream |
| Canada | S&P/TSX 60 | 198 201 | MVX/VIXC/ S&P/TSX 60 VIX* | 200 212 | Canada Derivatives Exchange |
| France | CAC 40 | 198 707 | VCAC | 200001* | DataStream |
| Germany | DAX | 196 501 | V1X | 199 201 | DataStream |
| Hong Kong | Hengsheng | 196 407 | VHSI | 200 101 | Bloomberg |
| Japan | Nikkei 225 | 195 004 | JNIV | 199 801 | DataStream |
| Netherlands | AEX | 198 301 | VAEX | 200001* | DataStream |
| Switzerland | SMI 20 | 198 806 | VSMI/V3X | 199 901 | DataStream |
| United Kingdom | FTSE 100 | 198 401 | VFTSE/IVUK30* | 200 001 | DataStream/Bloomberg |
| United States | S&P 500 | 196 401 | VIX | 199 001 | DataStream |

$J^{CW}_{n,T}$. A rejection of the null hypothesis means that the out-of-sample forecast based on the VRP model is more accurate than that using historical average returns.

Next, we follow Diebold and Mariano (2002) and Giacomini and White (2006) to compute the test statistic $J^{DM}_{n,T}$ as a finite sample predictive ability test. Compared to the population-level test, this finite sample test hurdle is much higher: the larger model may be more accurate than the smaller model in the population but not in the finite sample due to imprecise parameter estimation in the finite sample. We calculate and provide the $p$-values associated with the test statistic $J^{DM}_{n,T}$. A rejection of the null hypothesis means that the out-of-sample forecast based on the VRP model is more accurate than that using historical average returns, even after penalizing for additional finite sample estimation errors.

## 3. Data

Our main sample period is from January 2006 to December 2023, for a total of 216 months. We include data from nine emerging markets: Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan, which contribute to the majority of emerging market GDP. According to the IMF official website, in 2023, China, India, Brazil, Russia, Mexico, and South Korea were the top six contributors to GDP among emerging markets, in a descending order. Poland, Taiwan, and South Africa were ranked 9th, 10th, and 16th, respectively, among emerging markets. We do not include other emerging markets primarily due to the unavailability of index option data. To benchmark our study to related research in international finance, we also collect data from eleven developed markets: Australia, Belgium, Canada, France, Germany, Hong Kong (HK), Japan, the Netherlands, Switzerland, the U.K., and the U.S.

### 3.1. Data on option-implied volatility

For each market, we obtain data on option-implied volatility (square root of variance) from various sources. Table 1 Panel A provides the name and the starting date for option-implied volatility, the corresponding underlying stock index, and the data source for option-implied volatility. Of the nine emerging markets, two stock indices started before 1990, and the other seven started between 1990 and 2004.

All the model-free option-implied volatility indices in emerging markets started after January 2003, with the South Korea VKOSPI (volatility index for KOSPI 200) as the earliest in January 2003, and China CIVIX (volatility index for SSE 50) as the latest in February 2015. From Panel A of Table 1, it is evident that the option-implied volatility time series are much shorter than the market index time series. We choose to start our sample from 2006 when four emerging market VRPs are available—South Korea, Mexico, Poland, and Russia. Most markets, such as Brazil, China, India, South Korea, Russia, and Taiwan, follow a similar approach to the Cboe's VIX construction, and the option-implied volatility is estimated by averaging the weighted prices of the near maturity index puts and calls over a wide range of strike prices. The remaining markets adopt different methodologies to compute option-implied market volatility. Although different markets adopt varying methodologies to compute the market volatility indices, all reflect implied volatility from option data. All option-implied volatility data are provided on the official websites of the exchanges and have high quality, with most of these options having good liquidity. Internet Appendix B provides more details.

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

### 3.2. Summary statistics on VRPs

Table 2 presents the summary statistics of VRPs in monthly percentage squared units in the nine emerging markets and eleven developed

**Table 2**
Summary statistics: Stock VRPs.
This table reports summary statistics of the monthly VRPs for nine emerging markets and eleven developed markets, as well as the EMVRP and DMVRP. The VRP is the difference between the option-implied variance and the conditional expectation of future realized variance in monthly percentage-squared form. The sample period is from January 2006 to December 2023. Panel A reports the observation (Obs), mean, standard deviation (StDev), skewness (Skew), kurtosis (Kurt), and AR(1) coefficients. Panel B reports the correlation matrix of EMVRP, DMVRP, and country-level VRPs, and the *p*-values of correlation coefficients in parentheses. The symbol "–" in Panel B denotes that there are no overlap VRP data between two markets.

Panel A: Summary statistics

| | Obs | Mean | StDev | Skew | Kurt | AR(1) |
|---|---|---|---|---|---|---|
| EMVRP and DMVRP | | | | | | |
| EMVRP | 216 | 8.27 | 44.38 | 7.60 | 70.93 | 0.64 |
| DMVRP | 216 | 8.32 | 19.55 | −1.84 | 25.09 | 0.19 |
| Emerging Markets | | | | | | |
| Brazil | 154 | 2.06 | 69.73 | −6.85 | 72.79 | −0.09 |
| China | 107 | 4.96 | 20.66 | 1.57 | 8.30 | 0.18 |
| India | 194 | 6.33 | 33.62 | 5.39 | 41.53 | 0.35 |
| South Korea | 216 | −0.66 | 20.45 | 1.84 | 16.62 | 0.46 |
| Mexico | 138 | 8.93 | 34.22 | 4.89 | 37.41 | 0.58 |
| Poland | 89 | 7.26 | 40.38 | 3.44 | 16.88 | 0.61 |
| Russia | 216 | 27.08 | 170.31 | 7.05 | 70.81 | 0.47 |
| South Africa | 203 | 6.58 | 16.24 | −0.02 | 14.26 | 0.50 |
| Taiwan | 205 | 3.61 | 19.09 | 1.58 | 20.33 | 0.07 |
| Developed Markets | | | | | | |
| Australia | 192 | 8.55 | 24.74 | 0.08 | 23.44 | 0.50 |
| Belgium | 59 | 3.86 | 40.14 | −2.02 | 12.47 | 0.36 |
| Canada | 216 | 9.68 | 18.12 | 2.10 | 19.24 | 0.18 |
| France | 180 | 3.44 | 21.73 | −1.69 | 13.89 | 0.14 |
| Germany | 216 | 7.22 | 18.42 | 0.26 | 12.14 | 0.25 |
| Hong Kong | 216 | 5.90 | 24.31 | 2.68 | 16.15 | 0.56 |
| Japan | 216 | 10.06 | 27.97 | 5.19 | 44.04 | 0.52 |
| Netherlands | 180 | 4.96 | 48.75 | −8.84 | 106.66 | 0.17 |
| Switzerland | 216 | 6.13 | 16.10 | 3.23 | 18.08 | 0.60 |
| United Kingdom | 216 | 7.12 | 19.94 | −1.68 | 27.45 | 0.40 |
| United States | 216 | 8.67 | 27.99 | −6.74 | 72.89 | 0.07 |

Panel B: Correlation matrix of VRPs

| | DMVRP | Brazil | China | India | South Korea | Mexico | Poland | Russia | South Africa | Taiwan | Australia | Belgium | Canada | France | Germany | Hong Kong | Japan | Netherlands | Switzerland | U.K. | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EMVRP | 0.11 (0.12) | 0.38 (0.00) | 0.88 (0.00) | 0.73 (0.00) | 0.74 (0.00) | 0.78 (0.00) | 0.68 (0.00) | 0.89 (0.00) | 0.45 (0.00) | 0.56 (0.00) | 0.58 (0.00) | 0.02 (0.89) | 0.21 (0.00) | 0.22 (0.00) | 0.55 (0.00) | 0.65 (0.00) | 0.68 (0.00) | 0.08 (0.31) | 0.75 (0.00) | 0.31 (0.00) | −0.25 (0.00) |
| DMVRP | | 0.70 (0.00) | 0.16 (0.10) | −0.20 (0.01) | 0.41 (0.00) | 0.48 (0.00) | 0.58 (0.00) | 0.01 (0.91) | 0.37 (0.00) | 0.19 (0.01) | 0.34 (0.00) | 0.91 (0.00) | 0.52 (0.00) | 0.82 (0.00) | 0.57 (0.00) | 0.40 (0.00) | 0.52 (0.00) | 0.45 (0.00) | 0.23 (0.00) | 0.75 (0.00) | 0.91 (0.00) |
| Brazil | | | 0.03 (0.79) | −0.59 (0.00) | 0.58 (0.00) | 0.26 (0.02) | 0.53 (0.00) | 0.01 (0.90) | 0.38 (0.00) | 0.19 (0.02) | 0.70 (0.00) | – – | −0.30 (0.00) | 0.67 (0.00) | 0.38 (0.00) | 0.03 (0.68) | −0.21 (0.01) | −0.24 (0.01) | −0.20 (0.01) | 0.55 (0.00) | 0.77 (0.00) |
| China | | | | 0.14 (0.16) | 0.15 (0.13) | 0.53 (0.00) | – – | −0.10 (0.30) | 0.12 (0.23) | 0.20 (0.04) | −0.03 (0.75) | – – | 0.22 (0.02) | 0.10 (0.42) | 0.15 (0.13) | 0.32 (0.00) | 0.21 (0.03) | 0.26 (0.03) | 0.31 (0.00) | 0.11 (0.26) | 0.10 (0.33) |
| India | | | | | 0.46 (0.00) | 0.57 (0.00) | 0.45 (0.00) | 0.61 (0.00) | 0.29 (0.00) | 0.55 (0.00) | 0.42 (0.00) | −0.23 (0.18) | 0.15 (0.04) | −0.18 (0.02) | 0.27 (0.00) | 0.54 (0.00) | 0.52 (0.00) | 0.06 (0.47) | 0.73 (0.00) | 0.09 (0.19) | −0.50 (0.00) |
| South Korea | | | | | | 0.67 (0.00) | 0.72 (0.00) | 0.57 (0.00) | 0.51 (0.00) | 0.67 (0.00) | 0.64 (0.00) | 0.24 (0.06) | 0.28 (0.00) | 0.50 (0.00) | 0.69 (0.00) | 0.68 (0.00) | 0.63 (0.00) | 0.22 (0.00) | 0.61 (0.00) | 0.53 (0.00) | 0.10 (0.14) |
| Mexico | | | | | | | 0.81 (0.00) | 0.73 (0.00) | 0.64 (0.00) | 0.39 (0.00) | 0.67 (0.00) | 0.42 (0.00) | 0.49 (0.00) | 0.43 (0.00) | 0.59 (0.00) | 0.77 (0.00) | 0.81 (0.00) | 0.22 (0.01) | 0.72 (0.00) | 0.51 (0.00) | 0.13 (0.14) |
| Poland | | | | | | | | 0.63 (0.00) | 0.67 (0.00) | 0.41 (0.00) | 0.64 (0.00) | 0.56 (0.00) | 0.66 (0.00) | 0.57 (0.00) | 0.58 (0.00) | 0.79 (0.00) | 0.87 (0.00) | 0.32 (0.00) | 0.67 (0.00) | 0.61 (0.00) | 0.22 (0.04) |
| Russia | | | | | | | | | 0.35 (0.00) | 0.39 (0.00) | 0.44 (0.00) | −0.01 (0.94) | 0.16 (0.02) | 0.16 (0.03) | 0.45 (0.00) | 0.51 (0.00) | 0.59 (0.00) | 0.02 (0.78) | 0.60 (0.00) | 0.20 (0.00) | −0.30 (0.00) |
| South Africa | | | | | | | | | | 0.36 (0.00) | 0.69 (0.00) | 0.48 (0.00) | 0.10 (0.17) | 0.53 (0.00) | 0.52 (0.00) | 0.48 (0.00) | 0.41 (0.00) | 0.37 (0.00) | 0.49 (0.00) | 0.62 (0.00) | 0.14 (0.05) |
| Taiwan | | | | | | | | | | | 0.49 (0.00) | 0.21 (0.15) | 0.16 (0.02) | 0.26 (0.00) | 0.50 (0.00) | 0.55 (0.00) | 0.48 (0.00) | 0.51 (0.00) | 0.62 (0.00) | 0.55 (0.00) | −0.11 (0.10) |
| Australia | | | | | | | | | | | | 0.22 (0.21) | −0.09 (0.20) | 0.42 (0.00) | 0.45 (0.00) | 0.55 (0.00) | 0.47 (0.00) | 0.23 (0.00) | 0.50 (0.00) | 0.55 (0.00) | 0.08 (0.26) |
| Belgium | | | | | | | | | | | | | 0.56 (0.00) | 0.85 (0.00) | 0.41 (0.00) | 0.40 (0.00) | 0.57 (0.00) | 0.78 (0.00) | 0.19 (0.14) | 0.88 (0.00) | 0.74 (0.00) |
| Canada | | | | | | | | | | | | | | 0.30 (0.00) | 0.34 (0.00) | 0.43 (0.00) | 0.58 (0.00) | 0.23 (0.00) | 0.41 (0.00) | 0.34 (0.00) | 0.37 (0.00) |
| France | | | | | | | | | | | | | | | 0.73 (0.00) | 0.36 (0.00) | 0.41 (0.00) | 0.43 (0.00) | 0.20 (0.01) | 0.73 (0.00) | 0.69 (0.00) |
| Germany | | | | | | | | | | | | | | | | 0.53 (0.00) | 0.55 (0.00) | 0.33 (0.00) | 0.63 (0.00) | 0.62 (0.00) | 0.31 (0.00) |
| Hong Kong | | | | | | | | | | | | | | | | | 0.75 (0.00) | 0.24 (0.00) | 0.65 (0.00) | 0.47 (0.00) | 0.07 (0.28) |
| Japan | | | | | | | | | | | | | | | | | | 0.37 (0.00) | 0.72 (0.00) | 0.56 (0.00) | 0.16 (0.02) |
| Netherlands | | | | | | | | | | | | | | | | | | | 0.29 (0.00) | 0.80 (0.00) | 0.26 (0.00) |
| Switzerland | | | | | | | | | | | | | | | | | | | | 0.46 (0.00) | −0.12 (0.08) |
| U.K. | | | | | | | | | | | | | | | | | | | | | 0.51 (0.00) |

markets from January 2006 to December 2023.[5] In Panel A, we compute the EMVRP and DMVRP, and present their summary statistics in the first two rows. The time-series means are 8.27 and 8.32 for the EMVRP and DMVRP, respectively. The EMVRP (with a standard deviation of 44.38) is much more volatile than the DMVRP (with a standard deviation of 19.55), with a larger positive skewness and a much fatter tail. The AR(1) coefficient of DMVRP is 0.19, which is much smaller than that of EMVRP (0.64), indicating that the EMVRP is much more persistent than the DMVRP.[6]

[5] We also provide the summary statistics of option-implied and realized variances in Internet Appendix C Table C1.

[6] The lengths of country-level VRP data vary across countries. Our EMVRP measure aggregates country-level VRPs from all emerging markets with

The fact that option-implied variance is on average higher than realized variance in almost all markets directly leads to the mostly positive VRPs, ranging from a low of −0.66 (South Korea) to a high of 27.08 (Russia). In developed markets, we find that the averages of all country-level VRPs are positive. Japan has the largest mean of 10.06, while Canada has the smallest mean of 3.44. The average U.S. VRP is 8.67.

Panel B of Table 2 reports the correlations and $p$-values among the EMVRP, DMVRP, and country-level VRPs in the nine emerging markets and eleven developed markets. At the top of the table, the correlation between the EMVRP and the DMVRP is merely 11% ($p$-value = 0.12), indicating that the VRPs from emerging and developed markets are substantially different.[7] The VRPs in emerging markets are largely and positively correlated, ranging from a low correlation of −0.59 (Brazil and India) to a high correlation of 0.81 (Poland and Mexico). In developed markets, besides the U.S. and Switzerland, Australia and Canada, all correlations are positive. The smallest correlation is 0.07 (the U.S. and Hong Kong), and the largest correlation is 0.88 (the U.K. and Belgium). The correlations among developed markets are generally higher than those among emerging markets, suggesting that developed markets are perhaps more integrated than emerging markets.

Fig. 2 displays the time-series plots of monthly country-level VRPs in each market. The time series of VRPs appear to capture major economic events around the world. During the 2008 global financial crisis period, the VRPs in all emerging markets became exceptionally large and positive. For instance, Russia had a large and positive spike at 1,800 squared percent, mostly because oil prices plummeted at the same time as the global financial crisis, and Russia is a major oil exporter. The VRPs in developed markets were also exceptionally large, with negative spikes for half of them. During the 2011 European sovereign debt crisis, only some emerging markets, such as South Korea, were largely adversely affected, while common peaks in VRPs were observed in all developed markets. During the 2020 COVID-19 crisis period, the VRPs exhibited large spikes in six out of nine emerging markets, with half of them experiencing negative spikes. We detect large and negative spikes in VRPs in all developed markets.

There are also some country-specific events leading to dynamics of these VRP measures, but with little spill-over effect on other markets. For example, in June 2015, China experienced substantial spikes in VRPs. In February 2022, the VRPs in Russia had substantial spikes due to the Russia–Ukraine conflict. However, there were no obvious spikes in VRPs in all other emerging and developed markets around the same time.

Fig. 3 presents the time-series plots of EMVRP and DMVRP from January 2006 to December 2023.[8] Interestingly, these two VRP variables have distinct dynamics. The biggest spike for the EMVRP was around the 2008 global financial crisis, and the EMVRP was highly positive, at close to 460 squared percent. The biggest spike for the DMVRP also happened around 2008, yet the DMVRP was largely negative, at −150 squared percent. As suggested by Cheng (2019) and Lochstoer and Muir (2022), the different dynamics of EMVRP and DMVRP may stem from investors' perceptions of volatility news in different markets. The negative and positive spikes in the DMVRP may be attributed to initial underreaction and delayed overreaction to volatility news, while the large positive spikes in the EMVRP may result from overreaction to volatility news. There were other smaller spikes in both time series, such as the 2011 European sovereign debt crisis. We can detect the 2015 China market turbulence in the EMVRP—mainly due to the heavy weight of China in emerging markets' capitalization, and negative spikes in the DMVRP during the 2020 COVID-19 crisis period.

## 4. Empirical results

Prior research, such as Bollerslev et al. (2009), Drechsler and Yaron (2011), Bollerslev et al. (2014), Londono (2015), and Londono and Zhou (2017), shows that in the U.S. and other developed markets, the VRP is a powerful predictor for stock market returns and currency returns, possibly because the VRP captures aggregate economic uncertainty. In this section, we investigate whether the VRPs constructed from emerging markets contain relevant and differential information about future stock market returns and currency returns relative to the VRPs constructed from developed markets. In Section 4.1, we use the VRPs from individual markets, emerging markets, and developed markets to predict stock market returns. Then, we use these VRPs to predict currency returns in Section 4.2. Finally, we provide out-of-sample tests in Section 4.3 and one possible economic interpretation in Section 4.4.

### 4.1. Stock market return predictability

Predicting stock market returns or equity risk premiums has long been the focus of many previous studies. Empirical evidence to date suggests some predictability in stock market returns in the U.S., mainly for long horizons above one year.[9] However, future stock market returns are not easily predictable in the short-run horizon. Welch and Goyal (2008) examine many predictors for stock market returns in the U.S. and find that most of them have poor predictive power and are unstable both in-sample and out-of-sample. The variance risk premium proposed by Bollerslev et al. (2009), short rate by Rapach et al. (2016), implied volatility spread by Han and Li (2021), negative jump risk premium by Andersen et al. (2020), and option-implied tail risk by Andersen et al. (2021) are a few variables with significant and robust predictive power for future stock market returns. Here, our focus is on the emerging market variance risk premium (EMVRP).

#### 4.1.1. Emerging markets

We examine the stock market excess return predictability in nine emerging markets: Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan in U.S. dollars.[10] First, we estimate time-series regressions of stock market returns on country-level VRPs by market. Internet Appendix Table D1 reports the results. We find that country-level VRPs predict stock market returns in most markets, such as India, South Korea, Mexico, Poland, Russia, and Taiwan. Then, we present the estimation results from the panel regressions in Eq. (6) in Table 3. It shows the results based on country-level VRPs. We

available VRP data. Some might be concerned that the missing values of country-level VRPs might affect our results. To address this concern, we conduct a robustness check by computing the EMVRP using only country-level VRPs from South Korea and Russia, which are available throughout our whole sample. This new EMVRP has a correlation of 0.96 with the EMVRP used in the main results.

[7] To fully understand the dynamics of the correlation between the EMVRP and DMVRP, we also compute the 36-month rolling-window correlations between the two. These numbers have large variations between −0.10 and 0.84. In general, the correlations are smaller (larger) before (after) October 2011, with an average of −0.03 (0.41).

[8] Internet Appendix C Figure C1 shows the time-series plots of realized and option-implied variances.

[9] Examples include the dividend-price ratio (Campbell and Shiller, 1988a), earnings-to-price ratio (Campbell and Shiller, 1988b), book-to-market ratio (Kothari and Shanken, 1997), aggregate accruals and aggregate cash flows (Hirshleifer et al., 2009), market disagreement (Yu, 2011), implied cost of capital (Li et al., 2013), tail risk (Kelly and Jiang, 2014), and aggregate stock illiquidity (Chen et al., 2018).

[10] Our results remain similar when we predict stock market returns in local currencies instead of U.S. dollars, as indicated by the unreported results. We also use the log-difference to calculate cumulative returns, $r^i_{t,t+h} = (1/h)[\log(p^i_{t+h}) - \log(p^i_t)]$. Our findings are robust to these alternative measures of returns.

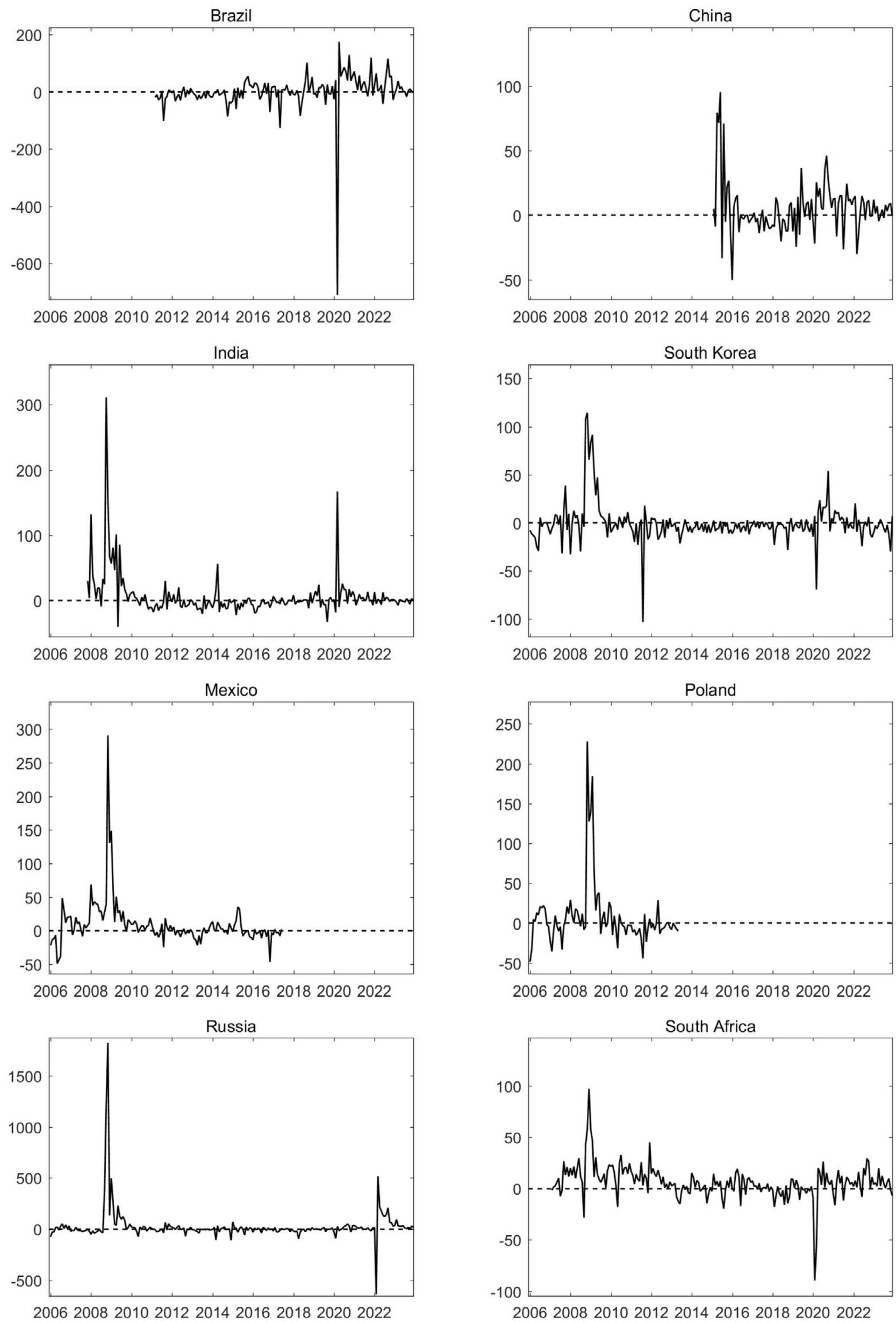


**Fig. 2.** Country-Level VRPs.
This figure plots the VRPs on a monthly percentage-squared basis in Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, Taiwan, Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S. The sample period is from January 2006 to December 2023.

find that the coefficients on $VRP^i$ become positive and statistically significant at the 5% level after 6 months. In terms of magnitude, for $h = 9$, one standard deviation increase in monthly $VRP^i$ leads to 5.20% increase in annualized excess stock returns over the next 9 months. The finding that $VRP^i$ in emerging markets can significantly predict its own future stock market returns is novel and consistent with the findings of previous studies in developed markets.

Next, we examine the predictive power of EMVRP. If there is some common component in emerging market country-level VRPs, then the EMVRP might significantly predict future stock market returns. If the common component of country-level VRPs contains more information about economic uncertainty in emerging markets than the country-level VRPs do, we might find that the adjusted $R^2$s using the EMVRP are higher than those using single market country-level VRPs. Interestingly,

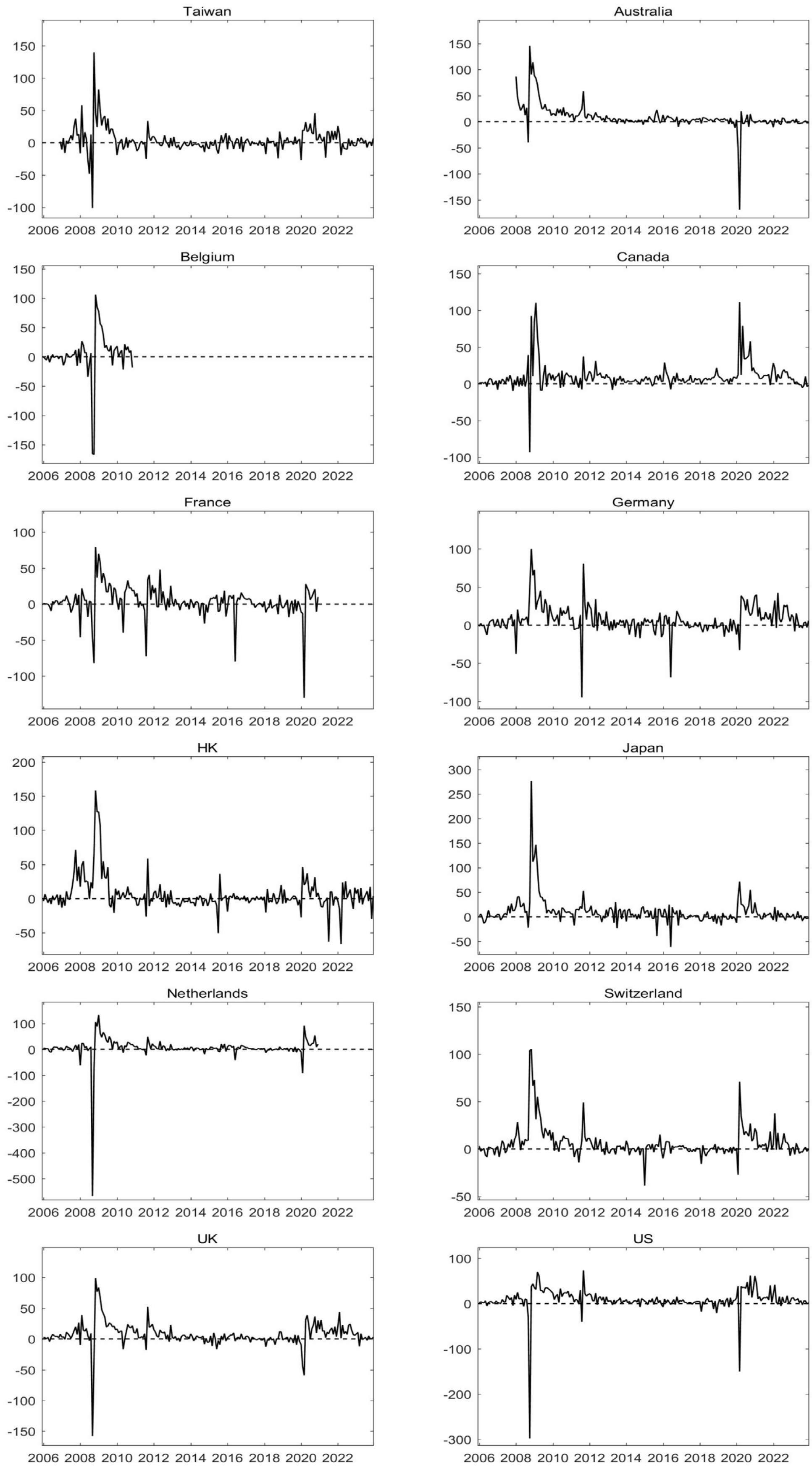


**Fig. 2.** (*continued*).

**Table 3**
Stock market return predictability in emerging markets.
This table provides panel regressions of the $h$-month ahead cumulative stock market index excess returns in the U.S. dollar, expressed in annualized percentage units, on the VRPs in nine emerging markets (Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan). The predictors include country-level VRPs, value-weighted EMVRP and DMVRP. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| $VRP^i$ | $b$ | −1.24 | −1.22 | 5.35 | 5.20 | 6.33 | 4.89 | 5.52 |
| | $t$(DC) | (−0.24) | (−0.31) | (1.78) | (2.37) | (4.20) | (4.61) | (5.37) |
| | $adj.R^2$ | −0.5% | −0.2% | 1.7% | 2.6% | 5.6% | 7.9% | 11.7% |
| EMVRP | $b$ | 0.70 | 1.53 | 10.89 | 11.04 | 10.48 | 7.19 | 7.26 |
| | $t$(DC) | (0.11) | (0.27) | (2.75) | (3.37) | (4.03) | (3.34) | (3.55) |
| | $adj.R^2$ | −0.4% | −0.3% | 5.1% | 7.3% | 9.1% | 8.5% | 14.2% |
| DMVRP | $b$ | 20.55 | 14.30 | 12.09 | 6.82 | 5.05 | 2.32 | 3.02 |
| | $t$(DC) | (2.27) | (2.26) | (2.03) | (1.13) | (1.02) | (0.67) | (0.87) |
| | $adj.R^2$ | 3.0% | 4.2% | 6.2% | 3.0% | 2.7% | 2.3% | 4.2% |
| EMVRP | $b_1$ | −1.52 | 0.00 | 9.72 | 10.43 | 10.06 | 7.02 | 7.02 |
| & | $t$(DC) | (−0.28) | (0.00) | (2.63) | (3.01) | (4.03) | (3.28) | (3.48) |
| DMVRP | $b_2$ | 20.71 | 14.30 | 11.06 | 5.71 | 3.99 | 1.58 | 2.26 |
| | $t$(DC) | (2.24) | (2.34) | (2.65) | (1.40) | (1.36) | (0.76) | (1.14) |
| | $adj.R^2$ | 2.9% | 4.1% | 10.2% | 9.1% | 10.3% | 8.7% | 15.3% |

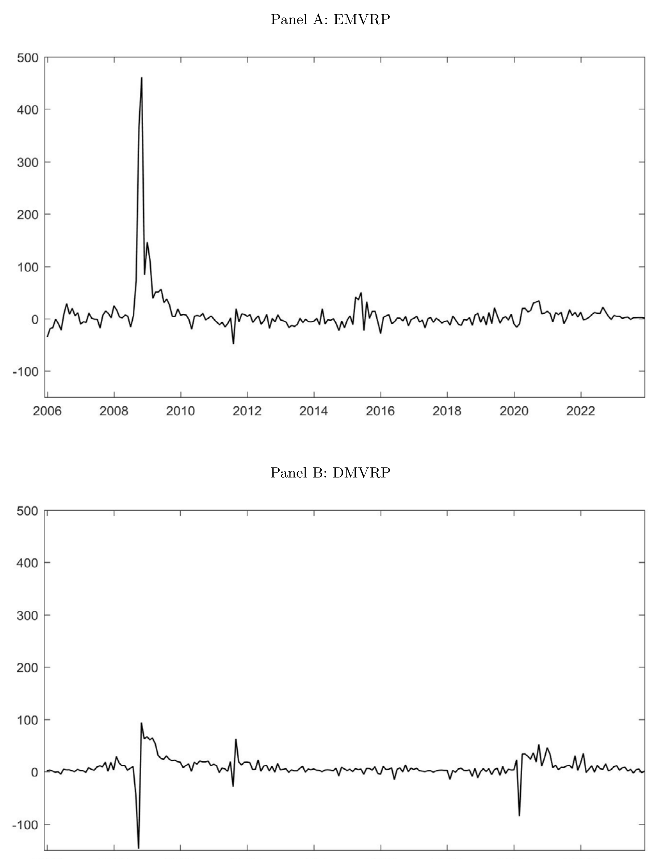


**Fig. 3.** Emerging Market and Developed Market VRPs
This figure shows the monthly EMVRP and DMVRP on a monthly percentage-squared basis from January 2006 to December 2023. The EMVRP and DMVRP are the market capitalization weighted average of country-level VRPs across nine emerging markets and eleven developed markets, respectively.

the coefficients on the EMVRP are significantly positive at the 1% significance level after 3 months. For instance, for the 6-month horizon, one standard deviation increase in monthly EMVRP would lead to 10.89% increase in annualized stock returns over the next 6 months. For horizons longer than 3 months, the coefficients range between 7.19 and 11.04. The adjusted $R^2$s using the EMVRP range from −0.4% to 14.2% for horizons from month 1 to month 24, peaking at 14.2% at month 24. The higher adjusted $R^2$s of EMVRP over the country-level VRPs indicate that the common component of emerging market country-level VRPs contains more information than the country-level VRPs for future stock market returns.[11]

Additionally, we investigate whether the common component of developed market country-level VRPs can predict future market returns in emerging markets. If the DMVRP is a global risk factor, then we would expect that the DMVRP can predict future emerging market country-level stock returns. We find that the coefficients on the DMVRP are positive and highly significant, 20.55, 14.30, and 12.09 at 1, 3, and 6 months. For instance, for 1 month ahead, the coefficient is 20.55, indicating that one standard deviation increase in monthly DMVRP would lead to 20.55% increase in annualized stock returns in the next 1 month. The adjusted $R^2$s range between 2.3% and 6.2%, peaking at month 6. The adjusted $R^2$s of DMVRP are 1.2%–4.4% higher than those of EMVRP for horizons less than 6 months. This pattern is consistent with the finding in Bollerslev et al. (2014) that the predictive power of DMVRP is particularly strong over short horizons.[12]

Finally, given that the correlation between the EMVRP and the DMVRP is only 11%, it is interesting to clarify which of the two has stronger predictive power for future stock market returns. In other words, it is important to differentiate the information content of EMVRP and DMVRP for future stock market returns. Therefore, we include both to predict emerging stock market returns. On the one hand, including the DMVRP weakens the statistical significance of EMVRP for shorter horizons from 1 to 3 months, but the EMVRP stays positive and significant after 3 months. On the other hand, including the EMVRP diminishes the magnitude of DMVRP, mainly for longer horizons. The coefficients on the EMVRP are higher than those on the DMVRP by the magnitude of 4.73–6.07 after 6 months. In other words,

[11] We also conduct time-series regressions of future stock market excess returns on the EMVRP by market and present the results in Internet Appendix D Table D2. We find that the EMVRP can still significantly predict returns for most horizons in all nine emerging markets.

[12] We conduct a bootstrap analysis to compare the $R^2$s between the EMVRP and DMVRP. We bootstrap 50,000 samples with replacement. For each bootstrap sample, we estimate the panel regressions of market excess returns or currency returns in nine emerging markets on the EMVRP with market fixed effects and calculate the adjusted $R^2$s. We find that the adjusted $R^2$s of DMVRP in the data are lower than the 5% or 10% lower quantiles of bootstrap $R^2$ of EMVRP over longer horizons.

**Table 4**
Stock market return predictability in developed markets.
This table provides panel regressions of the $h$-month ahead cumulative stock market index excess returns in the U.S. dollar, expressed in annualized percentage units, on the VRPs in eleven developed markets (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S.). The predictors include country-level VRPs, value-weighted EMVRP and DMVRP. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| $VRP^i$ | $b$ | 12.14 | 6.40 | 7.43 | 5.53 | 3.77 | 2.21 | 2.53 |
| | $t$(DC) | (2.30) | (2.05) | (3.85) | (3.15) | (2.49) | (2.27) | (2.22) |
| | $adj.R^2$ | 2.7% | 2.3% | 6.2% | 5.5% | 4.4% | 4.9% | 8.9% |
| EMVRP | $b$ | 0.07 | −1.70 | 4.22 | 5.11 | 4.51 | 2.62 | 2.90 |
| | $t$(DC) | (0.01) | (−0.53) | (1.75) | (3.16) | (4.08) | (3.05) | (3.30) |
| | $adj.R^2$ | −0.4% | 0.0% | 2.1% | 4.9% | 5.9% | 5.1% | 9.1% |
| DMVRP | $b$ | 12.90 | 7.61 | 7.52 | 4.23 | 2.57 | 1.24 | 1.64 |
| | $t$(DC) | (1.98) | (1.90) | (2.38) | (1.38) | (1.03) | (0.77) | (1.02) |
| | $adj.R^2$ | 3.2% | 3.4% | 6.6% | 3.4% | 2.3% | 2.5% | 5.0% |
| EMVRP | $b_1$ | −1.33 | −2.54 | 3.46 | 4.71 | 4.29 | 2.52 | 2.76 |
| & | $t$(DC) | (−0.35) | (−0.65) | (1.51) | (2.83) | (3.86) | (2.67) | (2.95) |
| DMVRP | $b_2$ | 13.04 | 7.88 | 7.15 | 3.73 | 2.11 | 0.97 | 1.34 |
| | $t$(DC) | (1.98) | (2.02) | (2.69) | (1.67) | (1.25) | (0.83) | (1.27) |
| | $adj.R^2$ | 3.2% | 3.8% | 8.0% | 7.2% | 7.0% | 5.5% | 10.3% |

the EMVRP dominates the DMVRP in return predictability over longer horizons after 6 months. In terms of the adjusted $R^2$s, including both variables clearly increases the overall explanatory power. The adjusted $R^2$s become 3.9%–11.1% higher than those with the DMVRP alone after 3 months, indicating that the EMVRP yields higher explanatory power than the DMVRP. Overall, the predictive powers of DMVRP and EMVRP are distinct and complementary, with the DMVRP significant up to 6 months, and the EMVRP mostly significant over longer horizons up to 24 months.[13]

#### 4.1.2. Developed markets

To further examine the predictive power of EMVRP, we expand the testing sample to include eleven developed markets (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland, the U.K., and the U.S.), and report the results in Table 4. We use the EMVRP to predict stock market returns. Surprisingly, even in eleven developed markets, the EMVRP still has positive and significant predictive power for stock market returns for horizons longer than 6 months. The coefficients range between 2.62 and 5.11, indicating that one standard deviation increase in monthly EMVRP would lead to 2.62%–5.11% increase in annualized stock returns after 6 months. The adjusted $R^2$s range between 4.9% to 9.1%, peaking at month 24.

For comparison, we include only the DMVRP in the panel regression. Compared with the EMVRP, which is significant over long horizons, the coefficients on the DMVRP are positive and significant over short horizons, 12.90 and 7.52 at 1 and 6 months. The adjusted $R^2$s range between 2.3% and 6.6%, smaller than those of EMVRP over longer horizons. Finally, we include both the EMVRP and DMVRP in panel regressions. The slope coefficients on the EMVRP are 0.98–2.18 higher than the DMVRP after 6 months. The results confirm those in Table 3, even with the eleven developed markets included.

#### 4.1.3. Global markets

Do the above patterns hold in all MSCI developed and emerging markets? To construct the MSCI sample, we further include fourteen MSCI emerging markets (Chile, Colombia, the Czech Republic, Egypt, Greece, Hungary, Indonesia, Malaysia, Peru, the Philippines, Qatar, Thailand, Turkey, and the United Arab Emirates) and twelve MSCI developed markets (Austria, Denmark, Finland, Ireland, Israel, Italy, New Zealand, Norway, Portugal, Singapore, Spain, and Sweden). In total, we have forty-six markets, consisting of twenty-three emerging markets and twenty-three developed markets.

We report the results in Table 5. First, we use the EMVRP to predict country-level stock market returns. Surprisingly, even with all MSCI developed and emerging markets, the common component of emerging market country-level VRPs still has positive and significant predictive power for country-level stock market returns for horizons longer than 3 months. The coefficients range from 4.90 to 7.90, indicating that one

[13] We further conduct the following robustness tests. First, we conduct panel regressions with additional year fixed effects and present the results in Internet Appendix D Table D3. We find that the results are robust. The EMVRP has significant and positive coefficients over longer horizons, while the DMVRP has significant and positive coefficients over shorter horizons. Second, we conduct an orthogonalized regression to examine whether country-specific VRPs are still relevant in the presence of common components in VRPs. Specifically, we estimate country-specific VRPs by regressing country-level VRPs on the EMVRP and DMVRP, with the residual part being orthogonal to the common component and representing country-specific VRPs. We report these results in Internet Appendix D Table D4. We find that country-specific VRPs carry negative signs over shorter horizons and have positive and significant coefficients over longer horizons in the presence of EMVRP and DMVRP for stock return predictability. In the presence of EMVRP and DMVRP, the coefficients on country-specific VRPs are insignificant over all horizons for currency return predictability. We also estimate the orthogonalized DMVRP by regressing the DMVRP on the EMVRP, with the residual part representing the DM-specific VRP. We find that the DM-specific VRP has significant coefficients over short horizons, while the EMVRP has significant coefficients over long horizons, consistent with our main results. Third, when constructing the EMVRP, we exclude China and Russia, which have large weights and spikes. Its correlation with the EMVRP in the main results is 0.84. The panel regression results show that the new EMVRP still has significant predictive power for future returns over long horizons. Fourth, we construct a new EMVRP with only Brazil, China, India, South Korea, Russia, and Taiwan, all of which adopt the Cboe's model-free method and use OTM options, called the OTM EMVRP. Its correlation with the EMVRP in the main results is 0.997. The panel regression result shows that the OTM EMVRP has significant predictive power for future returns over long horizons. Additionally, we construct the EMVRP using Mexico, Poland, and South Africa's ATM volatilities, called the ATM EMVRP. It is correlated with the EMVRP in the main results (correlation coefficient = 0.64). We estimate panel regressions using the ATM EMVRP and find that it has much weaker predictive power with lower statistical inference and a lower $R^2$ compared with the OTM EMVRP. After including the DMVRP in the regression, the coefficients on the ATM EMVRP become insignificant for all horizons in return predictability.

**Table 5**
Stock market return predictability in all MSCI markets.
This table provides panel regressions of the $h$-month ahead cumulative stock market excess returns in the U.S. dollar, expressed in annualized percentage units, on the VRPs in all MSCI developed and emerging markets. In addition to the nine emerging markets and eleven developed markets with available option-implied variance data in our sample, we include 14 emerging markets (Chile, Colombia, Peru, the Czech Republic, Egypt, Greece, Hungary, Qatar, Turkey, the United Arab Emirates, Indonesia, Malaysia, the Philippines, and Thailand) and 12 developed markets (Austria, Denmark, Finland, Ireland, Israel, Italy, Norway, Portugal, Spain, Sweden, New Zealand, and Singapore). The predictors include the value-weighted EMVRP and DMVRP. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| EMVRP | $b$ | 0.85 | 0.32 | 7.25 | 7.90 | 7.04 | 4.90 | 5.07 |
| | $t$(DC) | (0.14) | (0.08) | (2.42) | (3.78) | (4.70) | (3.76) | (4.17) |
| | $adj.R^2$ | −0.3% | 0.0% | 3.9% | 6.9% | 8.2% | 8.5% | 13.5% |
| DMVRP | $b$ | 15.97 | 10.11 | 9.39 | 5.32 | 3.55 | 2.12 | 2.21 |
| | $t$(DC) | (2.17) | (2.18) | (2.25) | (1.30) | (1.04) | (0.86) | (0.91) |
| | $adj.R^2$ | 2.9% | 3.6% | 6.3% | 3.5% | 3.0% | 3.8% | 6.0% |
| EMVRP | $b_1$ | −0.87 | −0.77 | 6.32 | 7.42 | 6.74 | 4.73 | 4.89 |
| & | $t$(DC) | (−0.21) | (−0.16) | (2.22) | (3.44) | (4.38) | (3.33) | (3.74) |
| DMVRP | $b_2$ | 16.06 | 10.20 | 8.72 | 4.53 | 2.84 | 1.61 | 1.69 |
| | $t$(DC) | (2.16) | (2.26) | (2.87) | (1.75) | (1.47) | (1.12) | (1.34) |
| | $adj.R^2$ | 2.9% | 3.6% | 8.9% | 8.9% | 9.3% | 9.1% | 14.5% |

standard deviation increase in monthly EMVRP would lead to 4.90%–7.90% increase in annualized stock returns after 3 months. The adjusted $R^2$s range from −0.3% to 13.5%, peaking at month 24.

Next, we include only the DMVRP. Quite different from the EMVRP, which is significant over longer horizons, the coefficients on the DMVRP range between 9.39 and 15.97 over shorter horizons within 6 months, which are significant at the 5% level. It indicates that the DMVRP is a significant short-run predictor. The adjusted $R^2$s range between 2.9% and 6.3%, which are about 3.4%–7.5% smaller than those for the EMVRP over longer horizons after 6 months.

Finally, we combine both the EMVRP and the DMVRP. The results confirm those in Tables 3 and 4, even though we include all MSCI developed and emerging markets. The slope coefficients on the EMVRP are always significant and positive, ranging between 4.73 and 7.42 over longer horizons after 3 months, indicating its importance as a common risk factor for all markets and more so for horizons longer than 3 months. The DMVRP is also very important, especially for horizons up to 6 months, for which it is always positive and statistically significant. The coefficients on the DMVRP range between 8.72 and 16.06 in the first 6 months, with a magnitude about 2.39–16.93 higher than those on the EMVRP. However, for horizons longer than 6 months, the explanatory power of DMVRP is dominated by the EMVRP, and the coefficients on the DMVRP become less significant or insignificant.

Overall, Tables 3, 4, and 5 confirm the existing empirical evidence that a higher (lower) VRP tends to be associated with higher (lower) stock returns over the next 1 to 24 months. The common component of country-level VRPs in the global capital market is quite important for future stock return prediction in both emerging and developed markets. The DMVRP is more important over shorter horizons, while the EMVRP is more important over longer horizons, implying that they contain differential and complementary information about current economic uncertainty relevant to future equity market risk premiums.

### 4.2. Currency return predictability

Other than stock index return predictability, currency return predictability, which heavily affects capital flows across borders, has also been extensively studied in the literature. Unfortunately, forecasting exchange rate returns has long been a tough challenge for industry practitioners as well as academic researchers for decades. The efforts are particularly futile over short horizons (e.g., Hansen and Hodrick, 1980; Meese and Rogoff, 1983; Chinn and Meese, 1995; Rogoff and Stavrakeva, 2008; Rogoff, 2009). Recently, Londono and Zhou (2017) show that both currency and stock variance risk premiums are the most powerful predictors for time variation in exchange rate returns over short horizons. Now our question becomes: Does the emerging market variance risk premium (EMVRP) provide new and additional information for currency return forecasts, relative to the developed market variance risk premium (DMVRP)?

#### 4.2.1. Emerging markets

In this section, we use stock VRPs to predict currency returns over short horizons, following Londono and Zhou (2017). First, we estimate time-series regressions of currency returns on country-level VRPs by market. Internet Appendix Table D5 reports the results. We find that country-level VRPs predict currency returns in most markets, such as India, South Korea, Poland, South Africa, and Taiwan. Then, Table 6 provides the results for panel regressions. After controlling for the interest rate differential for three-month interbank rates between the U.S. and foreign markets, we find that the coefficients on $VRP^i$ are less than 1, with $t$-statistics less than 1.96 over all horizons. It means that country-level VRPs have no significant predictive power for currency returns over all horizons considered.

Next, we show the results for currency return predictability with the EMVRP. The coefficients on the EMVRP are positive and significant, ranging from 1.53 to 1.93, with $t$-statistics greater than 1.96 after 6 months, even after controlling for the interest rate differentials between the U.S. and foreign markets. This indicates that one standard deviation increase in monthly EMVRP would lead to 1.53%–1.93% increase in annualized currency returns after 6 months with other controls remaining constant. The adjusted $R^2$s monotonically increase from 3.6% at month 9 to 13.4% at month 24.

For comparison, we only include the DMVRP in the panel regression. The DMVRP has the coefficients ranging from 0.90 to 7.20 from month 1 to month 24, which exhibits significant and positive predictive power for currency returns up to 6 months. For instance, for 1 month ahead, the coefficient is 7.20, indicating that one standard deviation increase in monthly DMVRP would lead to 7.20% increase in annualized currency returns in the next 1 month. The adjusted $R^2$s range between 2.5% and 10.0% from month 1 to month 24, with a peak arriving at month 6. The DMVRP has 0.3%–3.5% higher adjusted $R^2$s than the EMVRP for horizons less than 9 months.

We include both the DMVRP and the EMVRP. With the control of the interest rate differential, the coefficients on the EMVRP remain significantly positive, ranging from 1.46 to 1.80 over longer horizons after 9 months; while the coefficients on the DMVRP are positive and significant, ranging from 1.35 to 7.31 within 12 months. Additionally, the adjusted $R^2$s are about 0%–4.7% higher than those of DMVRP. The magnitude of coefficients on the EMVRP is about 0.46–0.70 higher than that of DMVRP after 9 months. The DMVRP and EMVRP seem to contain distinct and complementary predictive information for future currency returns, with the DMVRP more important up to 12 months, and the EMVRP more important over horizons beyond 9 months. This joint predictive pattern of EMVRP and DMVRP for currency returns mirrors that for stock market returns examined earlier.

Our results that the DMVRP has strong positive predictive power for foreign currency returns with respect to the U.S. dollar are consistent with the findings in Londono and Zhou (2017) that the U.S. stock VRP has positive 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 U.S. stock VRP is interpreted as a proxy for the country's domestic consumption growth uncertainty. Our novel finding additionally shows that the EMVRP is important for currency return prediction, and its predictive power dominates over longer horizons. This might seem sensible if the emerging market risk behaves more

 

**Table 6**
Currency return predictability in emerging markets.
This table provides panel regressions of the *h*-month ahead cumulative currency returns with respect to the U.S. dollar, expressed in annualized percentage units, on the VRPs in nine emerging markets (Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan). The predictors include country-level VRPs, value-weighted EMVRP and DMVRP. We control for the interest rate differential between the U.S. and each market. We report the coefficients on VRPs, *t*-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| $VRP^i$ | $b$ | −1.31 | −2.51 | −0.15 | −0.08 | 0.42 | 0.43 | 0.66 |
| | $t$(DC) | (−0.56) | (−1.25) | (−0.10) | (−0.08) | (0.59) | (1.06) | (1.75) |
| | $adj.R^2$ | −0.2% | 1.4% | 1.7% | 2.9% | 4.6% | 7.7% | 11.6% |
| EMVRP | $b$ | −0.40 | −1.31 | 1.82 | 1.93 | 1.93 | 1.53 | 1.58 |
| | $t$(DC) | (−0.17) | (−0.75) | (1.51) | (2.10) | (2.69) | (2.49) | (2.71) |
| | $adj.R^2$ | −0.3% | 0.5% | 2.0% | 3.6% | 5.5% | 8.1% | 13.4% |
| DMVRP | $b$ | 7.20 | 4.39 | 3.69 | 2.07 | 1.52 | 0.90 | 0.95 |
| | $t$(DC) | (2.68) | (2.57) | (2.70) | (1.76) | (1.59) | (1.21) | (1.30) |
| | $adj.R^2$ | 2.5% | 3.2% | 5.5% | 3.9% | 4.4% | 5.9% | 10.0% |
| EMVRP | $b_1$ | −1.12 | −1.76 | 1.48 | 1.75 | 1.80 | 1.46 | 1.50 |
| & | $t$(DC) | (−0.88) | (−0.86) | (1.20) | (1.77) | (2.46) | (2.23) | (2.46) |
| DMVRP | $b_2$ | 7.31 | 4.56 | 3.55 | 1.90 | 1.35 | 0.76 | 0.81 |
| | $t$(DC) | (2.69) | (2.72) | (3.19) | (2.24) | (2.38) | (1.70) | (1.87) |
| | $adj.R^2$ | 2.5% | 3.7% | 6.2% | 5.5% | 6.8% | 8.8% | 14.7% |

like rare disasters, such that the EMVRP is more persistent and predicts returns over longer horizons.[14]

### 4.2.2. Developed markets

Do the above patterns hold in developed markets as well? We expand our study on currency return prediction to include eleven developed markets. These currencies include Australia (AUD), the Euro Area (EUR), Canada (CAD), Japan (JPY), Switzerland (CHF), and the U.K. (GBP). Note that we drop Hong Kong due to its strictly pegged currency. We present the results in Table 7 and find that both the DMVRP and EMVRP are significant predictors for currency returns in developed markets. The coefficients on the EMVRP are positive and significant at the 5% level, ranging between 1.31 to 2.52 after 3 months. The adjusted $R^2$s increase from 0.5% at month 1 to 21.1% at month 24.

For comparison, we use the DMVRP to predict currency returns, all coefficients range between 2.98 and 6.23, with $t$-statistics above 1.74 up to 6 months. The adjusted $R^2$s range between 3.1% and 15.4% over all horizons, peaking at months 6 and 24. Finally, we include both the EMVRP and DMVRP in the panel regression. For horizons longer than 6 months, the explanatory power of DMVRP is dominated by the EMVRP. The coefficients on the EMVRP are 0.7–1.51 higher than those on the DMVRP after 6 months. These results confirm the findings in Table 6 that the EMVRP has more prominent predictive power than the DMVRP over longer horizons.

**Table 7**
Currency return predictability in developed markets.
This table provides panel regressions of the *h*-month ahead cumulative currency returns with respect to the U.S. dollar, expressed in annualized percentage units, on the VRPs in eleven developed markets. The currencies include Australia (AUD), the Euro Area (EUR), Canada (CAD), Japan (JPY), Switzerland (CHF), and the U.K. (GBP). The predictors include country-level VRPs, value-weighted EMVRP and DMVRP. We control for the interest rate differential between the U.S. and each market. We report the coefficients on VRPs, *t*-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| $VRP^i$ | $b$ | 5.05 | 3.10 | 3.39 | 2.58 | 2.15 | 1.54 | 1.76 |
| | $t$(DC) | (2.71) | (1.92) | (3.57) | (4.37) | (4.23) | (3.16) | (3.40) |
| | $adj.R^2$ | 2.1% | 3.6% | 8.7% | 9.5% | 11.1% | 14.0% | 21.7% |
| EMVRP | $b$ | 2.45 | 0.81 | 2.52 | 2.49 | 2.31 | 1.31 | 1.66 |
| | $t$(DC) | (0.98) | (0.78) | (2.44) | (3.13) | (3.97) | (2.28) | (3.05) |
| | $adj.R^2$ | 0.5% | 1.4% | 6.3% | 9.5% | 12.3% | 12.7% | 21.1% |
| DMVRP | $b$ | 6.23 | 3.20 | 2.98 | 1.56 | 0.95 | 0.68 | 0.85 |
| | $t$(DC) | (2.12) | (1.74) | (2.01) | (1.20) | (0.91) | (1.09) | (1.12) |
| | $adj.R^2$ | 3.1% | 3.8% | 7.5% | 6.5% | 7.3% | 10.2% | 15.4% |
| EMVRP | $b_1$ | 1.87 | 0.51 | 2.26 | 2.37 | 2.24 | 1.26 | 1.60 |
| & | $t$(DC) | (1.28) | (0.36) | (2.46) | (2.84) | (3.83) | (2.08) | (2.78) |
| DMVRP | $b_2$ | 6.05 | 3.15 | 2.76 | 1.33 | 0.73 | 0.56 | 0.69 |
| | $t$(DC) | (2.23) | (1.76) | (2.73) | (1.82) | (1.80) | (1.71) | (1.99) |
| | $adj.R^2$ | 3.3% | 3.8% | 10.0% | 10.7% | 12.8% | 13.2% | 22.2% |

### 4.2.3. Global markets

We expand our study on currency return prediction to all MSCI developed and emerging markets. Since there is no variation in currency returns for strictly pegged currencies, we drop markets with strictly pegged currencies, such as Hong Kong, Qatar, and United Arab Emirates, for currency return predictability. Table 8 presents the results. We find that both the DMVRP and EMVRP are significant predictors for currency returns in all MSCI developed and emerging markets. We first show the results for currency return predictability with the EMVRP. The coefficients on the EMVRP range from 1.48 to 2.30 after 3 months, which are positive and significant at the 5% level. This indicates that one standard deviation increase in monthly EMVRP leads to 1.48%–2.30% increase in annualized currency returns for horizons longer than 3 months. The adjusted $R^2$s increase from 0.3% at month 1 to 20.6% at month 24. Next, we use the DMVRP to predict currency returns and find that all coefficients are above 3, with $t$-statistics above 2.4 up to 6 months. The adjusted $R^2$s range between 3.0% and 15.9% over all horizons, with a peak at month 6. Finally, we combine both the EMVRP and the DMVRP. The coefficients on the EMVRP are positive and statistically significant after 3 months, with the magnitude about 0.77–1.21 higher than those on the DMVRP after 6 months. These results confirm those in Tables 6 and 7 that the predictive power of EMVRP is more prominent than that of DMVRP over longer horizons.

[14] Alternatively, we estimate panel regressions of future currency returns on VRPs by including two additional controls: the interest rate differential and world currency variance risk premiums. We do not report the results to save space. We find that the predictability patterns are similar to those in Table 6. Additionally, we predict currency returns using VRPs without any other controls. The unreported results show that the findings are similar to those in Table 6.

**Table 8**
Currency return predictability in all MSCI markets.
This table provides the panel regressions of the $h$-month ahead cumulative currency returns with respect to the U.S. dollar, expressed in the annualized percentage units, on the VRPs in all MSCI developed and emerging markets. In addition to the nine emerging markets and eleven developed markets with available option-implied variance data in our sample, we include 14 emerging markets (Chile, Colombia, Peru, the Czech Republic, Egypt, Greece, Hungary, Qatar, Turkey, the United Arab Emirates, Indonesia, Malaysia, the Philippines, and Thailand) and 12 developed markets (Austria, Denmark, Finland, Ireland, Israel, Italy, Norway, Portugal, Spain, Sweden, New Zealand, and Singapore). The sample includes 30 currencies after we exclude pegged currencies. The predictors include the value-weighted EMVRP and DMVRP. We control for the interest rate differential between the U.S. and each market. We report the coefficients on VRPs, $t$-statistics adjusted with standard with two-way clustering errors by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| EMVRP | $b$ | 1.16 | −0.20 | 2.22 | 2.30 | 2.13 | 1.48 | 1.62 |
| | $t$(DC) | (0.45) | (−0.16) | (2.39) | (3.45) | (4.69) | (3.28) | (3.71) |
| | $adj.R^2$ | 0.3% | 1.4% | 5.1% | 8.0% | 10.7% | 14.4% | 20.6% |
| DMVRP | $b$ | 6.60 | 3.59 | 3.14 | 1.60 | 1.04 | 0.63 | 0.70 |
| | $t$(DC) | (2.58) | (2.46) | (2.40) | (1.33) | (1.07) | (0.94) | (0.99) |
| | $adj.R^2$ | 3.0% | 3.8% | 7.0% | 6.3% | 7.6% | 11.6% | 15.9% |
| EMVRP | $b_1$ | 0.53 | −0.55 | 1.94 | 2.17 | 2.05 | 1.43 | 1.57 |
| & | $t$(DC) | (0.35) | (−0.35) | (2.16) | (3.06) | (4.48) | (3.01) | (3.43) |
| DMVRP | $b_2$ | 6.55 | 3.64 | 2.95 | 1.39 | 0.84 | 0.50 | 0.55 |
| | $t$(DC) | (2.63) | (2.51) | (3.16) | (1.84) | (1.74) | (1.34) | (1.55) |
| | $adj.R^2$ | 3.0% | 3.9% | 8.5% | 9.1% | 11.3% | 14.8% | 21.3% |

### 4.3. Out-of-sample tests

In Table 9, we present the out-of-sample (OOS) $R^2$ and $p$-values of the predictive accuracy tests for stock and currency returns. For the VRP model, we use one or a combination of DMVRP and EMVRP to forecast returns, whereas the benchmark model provides the prevailing mean forecast. We report two sets of $p$-values associated with the Clark and West (2007) (CW) test statistic defined in Internet Appendix A equation (A.1), and the Diebold and Mariano (2002) (DM) test statistic defined in Internet Appendix A equation (A.2). If the predictive power of VRP variables is robust out-of-sample, we expect to see positive OOS $R^2$s and the CW and DM $p$-values less than 5% or 10%.

Panel A reports the out-of-sample results for stock return predictability. The OOS $R^2$s of EMVRP are greater than 4.2%, with the CW $p$-value (DM $p$-value) less than 5% (10%) after 3 months, indicating that return prediction with the EMVRP is more accurate than that with the historical average over longer horizons. However, the OOS $R^2$s are negative within 3 months, meaning that return prediction with the EMVRP is less accurate than that with the historical average over shorter horizons. That is, the out-of-sample performance of EMVRP aligns with our main in-sample findings over longer horizons.

The OOS $R^2$s of DMVRP range between −4.3% and 2.4%. The CW $p$-value is greater than 5% for all horizons except for month 6, while the DM $p$-value is higher than 10% for all horizons. The OOS $R^2$s peak at the 6-month horizon at 2.4%, with the CW $p$-values less than 5%, echoing the superior in-sample predictive power of DMVRP over short horizons. For horizons longer than 3 months, the OOS $R^2$s of DMVRP are about 1.8%–11.8% lower than those of EMVRP.

When including both the DMVRP and the EMVRP as predictors, we find that their OOS $R^2$s are about 2.6%–7.0% higher than those of DMVRP alone after 3 months. The CW $p$-value is less than 5% after 3 months, whereas the DM $p$-value is less than 5% in 12 months. Between the CW and DM tests, we find that the $p$-values are in general higher for the DM tests because the DM tests penalize the imprecise parameter estimation in the finite sample.

Panel B provides the out-of-sample results for currency return predictability. The results follow a similar pattern to those in Panel A but are in general weaker. When we include only the EMVRP, it outperforms the historical mean benchmark with positive OOS $R^2$s, ranging from 1.2% to 5.5% after 3 months, with the CW $p$-value (DM $p$-value) less than 10% after 3 months.

**Table 9**
Out-of-Sample tests in emerging markets.
This table provides the out-of-sample (OOS) $R^2$s for panel regressions of the $h$-month ahead cumulative stock market excess returns in the U.S. dollar and cumulative currency returns with respect to the U.S. dollar on the VRPs in nine emerging markets. The predictors include the value-weighted EMVRP and DMVRP. The in-sample estimation period is from January 2006 to December 2010. The out-of-sample performance period is from January 2011 to December 2023. The OOS $R^2$ is $1-\frac{MSFE_2}{MSFE_1}$, where $MSFE_1$ is the mean squared forecast error for the benchmark using historical average, and $MSFE_2$ is the mean squared forecast error of a predictive regression based on the VRPs. The hypothesis is that $H_0$: $MSFE_1 \leq MSFE_2$; $H_1$: $MSFE_1 > MSFE_2$. The CW $p$-value is calculated from a standard normal distribution with one-tail hypothesis test following Clark and West (2007). The DM $p$-value is calculated from the statistics from Diebold and Mariano (2002). Panel A reports the results for predicting stock market returns in annualized percentage units. Panel B reports the results for predicting cumulative currency returns with respect to the U.S. dollar in annualized percentage units without controls.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Stock market returns | | | | | | | | |
| EMVRP | OOS $R^2$ | −0.2% | −0.1% | 4.2% | 6.5% | 8.2% | 7.8% | 7.5% |
| | CW $p$ | 0.93 | 0.72 | 0.01 | 0.01 | 0.00 | 0.01 | 0.03 |
| | DM $p$ | 0.93 | 0.74 | 0.03 | 0.02 | 0.01 | 0.03 | 0.10 |
| DMVRP | OOS $R^2$ | 0.3% | −0.3% | 2.4% | 1.8% | 1.9% | 0.1% | −4.3% |
| | CW $p$ | 0.19 | 0.12 | 0.01 | 0.11 | 0.08 | 0.27 | 0.45 |
| | DM $p$ | 0.47 | 0.53 | 0.32 | 0.34 | 0.29 | 0.49 | 0.79 |
| EMVRP | OOS $R^2$ | 0.6% | 0.2% | 5.0% | 6.9% | 8.6% | 7.1% | 1.0% |
| & | CW $p$ | 0.16 | 0.09 | 0.00 | 0.00 | 0.00 | 0.01 | 0.06 |
| DMVRP | DM $p$ | 0.43 | 0.48 | 0.17 | 0.08 | 0.02 | 0.06 | 0.44 |
| Panel B: Currency Returns | | | | | | | | |
| EMVRP | OOS $R^2$ | −0.3% | −0.7% | 1.2% | 2.1% | 3.1% | 3.7% | 5.5% |
| | CW $p$ | 0.88 | 0.89 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 |
| | DM $p$ | 0.88 | 0.91 | 0.05 | 0.06 | 0.05 | 0.06 | 0.05 |
| DMVRP | OOS $R^2$ | 1.6% | 1.1% | 2.8% | 1.8% | 1.8% | 1.0% | 1.0% |
| | CW $p$ | 0.04 | 0.02 | 0.00 | 0.03 | 0.01 | 0.03 | 0.04 |
| | DM $p$ | 0.19 | 0.25 | 0.10 | 0.20 | 0.11 | 0.19 | 0.30 |
| EMVRP | OOS $R^2$ | 1.3% | 0.7% | 3.3% | 3.2% | 4.2% | 4.2% | 5.5% |
| & | CW $p$ | 0.04 | 0.03 | 0.00 | 0.01 | 0.01 | 0.04 | 0.04 |
| DMVRP | DM $p$ | 0.21 | 0.32 | 0.09 | 0.10 | 0.05 | 0.11 | 0.14 |

For the DMVRP, the OOS $R^2$s are between 1.0% and 2.8%. The $p$-values for CW tests are less than 5% for all horizons. With both the DMVRP and the EMVRP as predictors, we find that their OOS $R^2$s range from 0.7% to 5.5%. The OOS $R^2$s are significant according to the CW $p$-values and about 0.5%–4.6% higher than those of DMVRP after 3 months.

Overall, both the EMVRP and DMVRP are important predictors for both stock market returns and currency returns in these out-of-sample tests. In most cases, they provide more accurate forecasts than the benchmark with the historical mean over different horizons. We find that the EMVRP outperforms the prevailing mean benchmark and clears the out-of-sample hurdle over longer horizons after 6 months, whereas the DMVRP outperforms the prevailing mean benchmark over most horizons. The EMVRP out-of-sample forecast performance is better than the DMVRP over longer horizons (after 3 months for stocks and after 6 months for currencies). Therefore, our main in-sample findings align with the out-of-sample tests.[15]

[15] We conduct additional two robustness tests for out-of-sample predictability. First, to downplay the older observations in the in-sample period, we employ weighted least squares. Second, we conduct encompassing tests between the EMVRP and the DMVRP. We report these results in Internet Appendix D Table D6 and find them similar to those in Table 9. Additionally, we measure the economic value of EMVRP's predictive ability from an asset allocation exercise in Internet Appendix D Table D6, and find that the EMVRP can generate sizable economic benefits in addition to the DMVRP.

**Table 10**
Return predictability in emerging markets with equal-weighted VRPs.
This table provides panel regressions of the $h$-month ahead cumulative stock market index excess returns and currency returns, expressed in annualized percentage units, on the VRPs in nine emerging markets (Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan). The predictors include the equal-weighted EMVRP and DMVRP. Panel A reports the results for predicting stock market index excess returns. Panel B provides the results for predicting currency returns after controlling for the interest rate differential between the U.S. and each market. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Stock market returns | | | | | | | | |
| EMVRP | $b$ | 1.60 | 3.10 | 11.67 | 11.18 | 10.34 | 6.80 | 7.45 |
| | $t$(DC) | (0.27) | (0.49) | (3.06) | (3.28) | (4.00) | (3.15) | (3.34) |
| | $adj.R^2$ | −0.4% | −0.1% | 5.8% | 7.5% | 8.9% | 7.7% | 14.3% |
| DMVRP | $b$ | 27.20 | 18.05 | 17.39 | 12.65 | 9.82 | 5.73 | 6.58 |
| | $t$(DC) | (2.48) | (2.50) | (4.59) | (3.02) | (2.79) | (2.19) | (2.49) |
| | $adj.R^2$ | 5.5% | 6.8% | 12.8% | 9.5% | 8.1% | 5.9% | 11.8% |
| EMVRP | $b_1$ | −17.80 | −8.97 | 3.45 | 6.26 | 7.17 | 5.24 | 5.42 |
| & | $t$(DC) | (−2.38) | (−1.45) | (1.09) | (1.75) | (2.91) | (2.47) | (2.65) |
| DMVRP | $b_2$ | 36.63 | 22.81 | 15.56 | 9.32 | 6.00 | 2.95 | 3.58 |
| | $t$(DC) | (3.31) | (3.87) | (3.92) | (2.14) | (1.85) | (1.27) | (1.55) |
| | $adj.R^2$ | 7.3% | 8.0% | 13.2% | 11.0% | 10.8% | 8.5% | 16.2% |
| Panel B: Currency returns | | | | | | | | |
| EMVRP | $b$ | 0.11 | −0.62 | 2.17 | 2.05 | 1.97 | 1.50 | 1.67 |
| | $t$(DC) | (0.05) | (−0.31) | (1.76) | (2.11) | (2.73) | (2.53) | (2.74) |
| | $adj.R^2$ | −0.3% | 0.3% | 2.5% | 3.9% | 5.6% | 7.9% | 13.7% |
| DMVRP | $b$ | 8.14 | 4.69 | 4.78 | 3.14 | 2.36 | 1.52 | 1.65 |
| | $t$(DC) | (2.34) | (2.00) | (4.31) | (3.61) | (3.46) | (2.78) | (3.02) |
| | $adj.R^2$ | 3.2% | 3.6% | 8.5% | 6.8% | 6.8% | 8.0% | 13.7% |
| EMVRP | $b_1$ | −5.67 | −4.21 | −0.43 | 0.58 | 1.02 | 0.97 | 1.08 |
| & | $t$(DC) | (−4.52) | (−2.12) | (−0.39) | (0.56) | (1.40) | (1.58) | (1.75) |
| DMVRP | $b_2$ | 11.11 | 6.91 | 5.01 | 2.84 | 1.82 | 1.02 | 1.06 |
| | $t$(DC) | (3.33) | (3.85) | (4.87) | (3.26) | (2.87) | (2.07) | (2.14) |
| | $adj.R^2$ | 4.4% | 5.6% | 8.5% | 6.9% | 7.4% | 8.9% | 15.2% |

### 4.4. Economic interpretation

Our main empirical results show that the predictive patterns of EMVRP and DMVRP are drastically different, with the former dominates return predictability beyond the six-month horizon, while the latter is more significant in the short run. What drives the differential predictive patterns of EMVRP and DMVRP, and what information is contained in these VRP variables? To understand these empirical findings, we develop a simple two-country (emerging market and developed market) international asset pricing model with partial market integration and heterogeneous economic uncertainty to provide one possible explanation. We assume that the developed market is fully integrated into the global economy, while the emerging market is only partially integrated, which is consistent with the literature on market integration, such as Bekaert and Harvey (1995). Internet Appendix E1 shows details on the model setup.

The model solution for the developed market is quite standard, and is presented in Internet Appendix E2. The model solution for the emerging market is a bit more complicated, and is presented in Internet Appendix E3. For our purpose, we focus on whether the EMVRP and the DVMRP can predict future returns. Internet Appendix E4 provides the solutions to model-implied $R^2$ for both emerging and developed markets. For the developed economy, which is fully integrated in the global market, the equity risk premium and the DMVRP are only influenced by the world growth volatility risk and the drifting economic uncertainty risk. In contrast, the emerging economy is not fully integrated into the world economy. Both the equity risk premium and the EMVRP are also influenced by the emerging market-specific growth volatility risk, in addition to the world growth volatility risk and the drifting economic uncertainty risk.

Next, we calibrate this model with parameters we observe in the data, and examine whether the model can generate the predictive patterns we observe in the data. Internet Appendix E5–E6 presents the calibration results and parameter sensitivity tests.

Intuitively, since the consumption growth in the emerging market is more volatile than that in the developed market observed in the data, economic uncertainty is more heavily priced in the emerging market. Due to the paramount importance of the drifting uncertainty component, the emerging market is more affected by the more persistent drifting uncertainty component rather than the volatility itself. The partial integration makes the EMVRP load even more on the more persistent component of economic uncertainty, and the loadings on the volatility itself for emerging market returns drop more quickly as the forecast horizon increases, which pushes the hump-shaped pattern in return predictability $R^2$ further to a longer horizon.

## 5. Robustness checks

In this section, we conduct a number of robustness checks. In Section 5.1, we use the equal-weighted scheme to measure the EMVRP and DMVRP. In Section 5.2, we predict returns period by period. In Section 5.3, we winsorize the EMVRP and DMVRP at the 5% level to control for the financial crisis. In Section 5.4, we estimate expected realized variance using different variance forecasting models.

### 5.1. Equal-weighted VRPs

When aggregating VRPs using market capitalization, the DMVRP is dominated by the U.S., and the EMVRP is dominated by China. The U.S. and China have dominant capitalization in these two markets. For our first robustness check, instead of using the value-weighted scheme, we use the equal-weighted scheme to construct the DMVRP and EMVRP to predict stock market returns and currency returns in nine emerging markets. Table 10 reports the results. We find that these two equal-weighted VRPs still have significant predictive power for stock market returns and currency returns. The coefficients on the EMVRP are positive and significant after 3 months for stock returns in Panel A and after 6 months for currency returns in Panel B. When

**Table 11**
Return predictability in emerging markets period-by-period.
This table provides panel regressions of the $h$-month ahead stock market index excess returns and currency returns, expressed in annualized percentage units, on the VRPs in nine emerging markets (Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan). The predictors include the value-weighted EMVRP and DMVRP. Panel A reports the results for predicting stock market excess returns. Panel B provides the results for predicting currency returns after controlling for the interest rate differential between the U.S. and each market. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Stock market returns | | | | | | | | |
| EMVRP | $b$ | 0.70 | 0.52 | 24.66 | 5.50 | 4.34 | −2.92 | 0.87 |
| | $t$(DC) | (0.11) | (0.06) | (7.61) | (0.93) | (1.52) | (−0.47) | (0.24) |
| | $adj.R^2$ | −0.4% | −0.4% | 4.5% | −0.2% | −0.3% | −0.4% | −0.5% |
| DMVRP | $b$ | 20.55 | 15.08 | −1.15 | −2.82 | −0.20 | −4.20 | −3.44 |
| | $t$(DC) | (2.27) | (2.13) | (−0.12) | (−0.41) | (−0.05) | (−0.83) | (−0.80) |
| | $adj.R^2$ | 3.0% | 1.4% | −0.4% | −0.4% | −0.4% | −0.3% | −0.4% |
| EMVRP | $b_1$ | −1.52 | −1.10 | 25.07 | 5.87 | 4.41 | −2.51 | 1.25 |
| & | $t$(DC) | (−0.28) | (−0.14) | (7.98) | (1.19) | (1.51) | (−0.46) | (0.46) |
| DMVRP | $b_2$ | 20.71 | 15.19 | −3.81 | −3.45 | −0.67 | −3.93 | −3.58 |
| | $t$(DC) | (2.24) | (2.31) | (−0.95) | (−0.59) | (−0.17) | (−0.90) | (−0.85) |
| | $adj.R^2$ | 2.9% | 1.4% | 4.6% | −0.1% | −0.3% | −0.3% | −0.4% |
| Panel B: Currency returns | | | | | | | | |
| EMVRP | $b$ | −0.40 | −2.16 | 6.72 | 1.39 | 1.54 | −0.98 | 0.02 |
| | $t$(DC) | (−0.17) | (−0.85) | (5.24) | (1.15) | (2.22) | (−0.39) | (0.02) |
| | $adj.R^2$ | −0.3% | 0.0% | 2.1% | −0.2% | −0.2% | −0.3% | −0.2% |
| DMVRP | $b$ | 7.20 | 5.71 | 0.12 | 0.53 | −0.05 | −1.27 | −1.28 |
| | $t$(DC) | (2.68) | (2.42) | (0.04) | (0.31) | (−0.04) | (−0.76) | (−0.70) |
| | $adj.R^2$ | 2.5% | 1.5% | −0.3% | −0.3% | −0.3% | −0.2% | −0.1% |
| EMVRP | $b_1$ | −1.12 | −2.75 | 6.78 | 1.35 | 1.56 | −0.87 | 0.15 |
| & | $t$(DC) | (−0.88) | (−1.38) | (5.40) | (1.07) | (2.23) | (−0.39) | (0.13) |
| DMVRP | $b_2$ | 7.31 | 5.98 | −0.54 | 0.40 | −0.21 | −1.19 | −1.29 |
| | $t$(DC) | (2.69) | (3.17) | (−0.42) | (0.26) | (−0.18) | (−0.79) | (−0.72) |
| | $adj.R^2$ | 2.5% | 1.8% | 2.1% | −0.3% | −0.2% | −0.2% | −0.2% |

we include both the EMVRP and the DMVRP, the predictive power of EMVRP is significant after 9 months for stock returns, and the DMVRP shows significant predictive power over short horizons. These findings are similar to the ones in Tables 3 and 6.[16]

### 5.2. Return predictability period-by-period

In our main analysis, we use VRPs to predict the $h$-month ahead cumulative stock and currency returns. Here, we aim to clarify the horizon dynamics of VRP measures by using them to predict returns over month $t + h$, instead of using cumulative values from $t + 1$ to $t + h$ on the left hand side of the panel regressions in Eqs. (6) and (7). Table 11 presents the results. For stock return predictability in Panel A, the coefficients on the EMVRP are positive and statistically significant at the 5% level at the 6-month horizon, while the coefficients on the DMVRP are significant and positive at the 5% level at 1 and 3 months. For currency return predictability in Panel B, the results are quite similar to those in Panel A. Comparing these results with the predictability of cumulative returns in Tables 3 and 6, we find that excluding the carryover effect from cumulative returns shortens the predictive horizon of VRPs. This is likely because cumulative measures reduce some noise. Nevertheless, the EMVRP has strong predictive power over longer horizons, while the DMVRP has strong predictive power over shorter horizons, consistent with our main findings in Tables 3 and 6.

[16] Additionally, we construct the EMVRP using the first principal component of four emerging market VRPs with the longest available data. We find that the EMVRP significantly predicts both stock and currency returns over longer horizons from the unreported results, which is consistent with our main findings.

### 5.3. Influential observations

The DMVRP has large negative values in October 2008 and large positive values in November 2008. The EMVRP also has large positive values in November 2008. These observations with large values are influential observations, which might contain valuable information. Therefore, we include these influential observations in our main analysis. To make sure that our main findings are not driven by these influential observations, we conduct two robustness tests by minimizing their impact. In the first approach, we winsorize the VRP measures at the 5% level and report the results in Table 12. For stock return predictability in Panel A, the coefficients on the DMVRP are positive and significant at the 5% level up to 12 months, while the coefficients on the EMVRP are positive and significant at the 5% level after 3 months. For currency return predictability in Panel B, the results are similar to those in Panel A. Still, the EMVRP has strong predictive power over longer horizons, while the DMVRP has strong predictive power over shorter horizons.

In the second approach, we compute the natural logarithm of the variance measures to minimize the impact of spikes. We measure country-level log VRPs as the difference between the natural logarithm of option-implied variance and the natural logarithm of expected realized variance. Subsequently, we obtain the aggregated EMVRP and DMVRP by value weighting country-level log VRPs. Due to space constraints, we do not report the results here, and they align with our main findings.

### 5.4. Different models to estimate expected realized variance

In the main results, our VRPs are estimated as the difference between the expected variance under the risk-neutral measure and the expected variance under the physical measure. The estimation of expected

**Table 12**
Return predictability in emerging markets after controlling for influential observations.
This table provides panel regressions of the $h$-month ahead cumulative stock market index excess returns and currency returns, expressed in annualized percentage units, on the VRPs in nine emerging markets (Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan). The predictors include the value-weighted EMVRP and DMVRP. The VRPs are winsorized at the 5% level to control for the influential observations in the global financial crisis period. Panel A reports the results for predicting stock market index excess returns. Panel B provides the results for predicting currency returns after controlling for the interest rate differential between the U.S. and each market. We report the coefficients, $t$-statistics adjusted with standard errors with two-way clustering by market and month (in parentheses), and adjusted $R^2$. The sample period is from January 2006 to December 2023.

| Predictor | | Horizons | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Stock market returns | | | | | | | | |
| EMVRP | $b$ | 7.42 | 9.47 | 11.66 | 9.64 | 8.74 | 6.49 | 6.15 |
| | $t$(DC) | (0.90) | (1.73) | (3.02) | (2.78) | (2.94) | (2.55) | (2.61) |
| | $adj.R^2$ | 0.0% | 1.7% | 5.8% | 5.7% | 6.6% | 7.1% | 10.6% |
| DMVRP | $b$ | 18.60 | 15.82 | 13.69 | 9.66 | 7.17 | 4.38 | 4.64 |
| | $t$(DC) | (2.57) | (3.32) | (3.51) | (2.46) | (2.14) | (1.69) | (1.95) |
| | $adj.R^2$ | 2.4% | 5.1% | 7.9% | 5.6% | 4.6% | 4.1% | 6.7% |
| EMVRP | $b_1$ | −4.29 | 0.95 | 5.91 | 6.23 | 6.93 | 5.93 | 5.32 |
| & | $t$(DC) | (−0.41) | (0.17) | (1.68) | (1.86) | (2.34) | (2.42) | (2.63) |
| DMVRP | $b_2$ | 21.00 | 15.29 | 10.35 | 6.15 | 3.25 | 1.01 | 1.45 |
| | $t$(DC) | (2.05) | (2.91) | (2.59) | (1.52) | (0.96) | (0.43) | (0.80) |
| | $adj.R^2$ | 2.4% | 5.1% | 8.8% | 7.1% | 7.1% | 7.2% | 10.9% |
| Panel B: Currency returns | | | | | | | | |
| EMVRP | $b$ | 1.54 | 1.54 | 2.62 | 1.99 | 1.86 | 1.89 | 1.96 |
| | $t$(DC) | (0.63) | (0.87) | (2.17) | (2.08) | (2.33) | (2.88) | (3.32) |
| | $adj.R^2$ | −0.1% | 0.6% | 3.2% | 3.7% | 5.3% | 9.8% | 16.1% |
| DMVRP | $b$ | 6.02 | 4.68 | 4.36 | 2.89 | 2.10 | 1.53 | 1.55 |
| | $t$(DC) | (2.61) | (3.27) | (4.41) | (3.43) | (2.95) | (2.58) | (2.72) |
| | $adj.R^2$ | 1.7% | 3.6% | 7.2% | 6.0% | 6.0% | 8.0% | 12.9% |
| EMVRP | $b_1$ | −2.60 | −1.52 | 0.31 | 0.57 | 1.02 | 1.52 | 1.64 |
| & | $t$(DC) | (−0.87) | (−0.82) | (0.26) | (0.57) | (1.27) | (2.29) | (3.06) |
| DMVRP | $b_2$ | 7.47 | 5.53 | 4.18 | 2.56 | 1.53 | 0.67 | 0.58 |
| | $t$(DC) | (2.41) | (3.40) | (3.77) | (2.71) | (2.17) | (1.20) | (1.26) |
| | $adj.R^2$ | 1.9% | 3.8% | 7.2% | 6.1% | 6.5% | 10.2% | 16.5% |

realized variance follows the specification of Bekaert and Hoerova (2014) and include six lagged predictors. To test the robustness of our main results to the measure of expected realized variance, we adopt two alternative variance forecasting models. The first model uses the predictors from the HAR model introduced by Corsi (2009), which includes the lagged natural logarithm of monthly, weekly, and daily realized variances. We present the results in Internet Appendix Table D7. For stock return predictability in Panel A, the coefficients on the DMVRP are positive and significant at the 5% level up to 9 months, while the coefficients on the EMVRP are positive and significant at the 5% level after 6 months. In Panel B, the results for currency return predictability closely resemble those in Panel A.

For the second model, in addition to the six lagged predictors in the benchmark model, we include macroeconomic variables, such as the CPI growth rate, unemployment rate, economic policy uncertainty of Baker et al. (2016), and GDP growth rate, in the predictive regressions. The results for predicting stock and currency returns are presented in Internet Appendix Table D8. Overall, we find that our main findings remain robust to the measure of expected realized variance. Specifically, the EMVRP has strong predictive power over longer horizons, while the DMVRP has strong predictive power over shorter horizons.

## 6. Conclusion

Many previous studies have examined the predictive power of VRPs for asset returns in developed markets. Yet, studying VRPs in emerging markets has been difficult due to the lack of risk-neutral variance data implied from index options. In this paper, we construct VRPs in nine emerging markets and examine for the first time the predictive power of EMVRP for stock market returns and currency returns.

We find that the DMVRP and EMVRP significantly predict future stock market returns and currency returns. More interestingly, in all in-sample predictive regressions, the DMVRP has stronger predictive power over shorter horizons, while the EMVRP has stronger predictive power over longer horizons. Additionally, these results are consistent with out-of-sample tests. It is clear that the two VRPs contain differential information content.

In a two-country model with partial market integration and drifting economic uncertainty, we can replicate the varying VRP predictability patterns—the predictive power of DMVRP peaks around four to five months, while that of EMVRP peaks around eight to ten months.

## CRediT authorship contribution statement

**Fang Qiao:** Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft. **Lai Xu:** Methodology, Validation. **Xiaoyan Zhang:** Conceptualization, Project administration, Supervision, Validation, Writing – review & editing. **Hao Zhou:** Conceptualization, Project administration, Supervision, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbankfin.2024.107259.

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