Global implied volatility and variance risk premium

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Abstract

Motivated by the global nature of financial risk, we propose a simple measure of global implied volatility (GIV) and show that it better describes international financial market dynamics than the VIX. Predictive evidence on both realized and implied volatilities around the world leads to the conclusion of truly global risk dynamics, not merely US spillovers. A direct global measure of variance risk premium based on GIV predicts expected excess returns in various international equity markets outperforming a previously proposed measure based on cross-country aggregation of local variance risk premia. We show that this is due to the international price of jump risk which is better captured by our global measure of variance risk premium. Foreign exchange markets confirm our findings. Currency portfolios based on our global variance risk premium generate significant value in excess of those based on aggregated local variance risk premia and the US variance risk premium.

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1. Introduction

Derived from option prices, implied volatility is widely viewed as investors' fear gauge (Whaley, 2000, 2009). Spikes in implied volatility typically coincide with anticipated market turbulence and bear a relationship with capital flows such as flight to safety dynamics (Adrian et al., 2019). As a result, implied volatility plays a central role to explain important financial markets facts. First, it is highly relevant for risk management since, by reflecting the market's risk-neutral expectation of future volatility, implied volatility is a natural predictor of realized volatility (Busch et al., 2011). Second, in asset pricing the gap between implied volatility and expected realized volatility, known as the variance risk premium (VRP), is a robust predictor of expected returns, and, given its interpretation of macroeconomic uncertainty (Bollerslev et al., 2009; Drechsler, 2013) or risk aversion (Bollerslev et al., 2011; Bekaert and Hoerova, 2016), it represents macro-financial linkages.

Financial risk, however, is global in nature. Cross-border capital flows, multinational production, and globally integrated markets imply that risk shocks rarely remain confined within national borders.[1] Often comovements in international financial markets have been depicted as a sign of interdependence among markets rather than financial contagion.[2] Theoretical frameworks in international finance and open-economy macroeconomics model these phenomena through global uncertainty or risk factors that drive comovements in returns, capital flows, and economic activity across countries.[3] For example, Cooper et al. (2022) show that global macroeconomic risk factors explain variation in international asset premia.

In practice, the VIX index, constructed from S&P 500 options, is widely used as a proxy for global financial uncertainty. Its appeal stems from the extensive empirical evidence documenting how US market information transmits globally. For example, Miranda-Agrippino and Rey (2020) find that the global financial cycle largely comoves with the VIX and it has been documented that US spillovers contain predictive power for both returns (Rapach et al., 2013; Londono, 2015) and volatilities (Buncic and Gisler, 2016) around the world.

Yet the VIX is inherently US-centric and may capture only part of the global risk embedded in option markets. The assumption that US implied volatility fully represents global uncertainty has rarely been tested systematically. While numerous studies document the transmission of US volatility to other markets, little evidence exists on whether a truly global implied volatility factor — extracted directly from international option markets — contains distinct and incremental predictive information for risk and returns dynamics around the globe. Londono and Wilson (2018) suggest that global risk is not simply a spillover from US dynamics: by analyzing forecast error variances decompositions, they find that global factors explain a larger share of

[1] See King and Wadhwani (1990), Lin et al. (1994), King et al. (1994), Karolyi (1995), Wongswan (2006), Diebold and Yilmaz (2009), Corradi et al. (2012) among many others documenting volatility spillovers.

[2] See, for example, Forbes and Rigobon (2002) Karolyi (2003), Jung and Maderitsch (2014), Barigozzi et al. (2019).

[3] Caggiano and Castelnuovo (2023) quantify the macroeconomic importance of global risk finding that global financial uncertainty shocks account for 13% of world's contraction in output during the Great Recession.

global volatilities than US variables. Recent evidence also highlights the importance of global uncertainty in driving expected equity returns across countries. Bollerslev et al. (2014) propose a global VRP measure accounting for stock return predictability beyond the US. Qiao et al. (2024) further show the empirical relevance of emerging markets' VRPs for international stock returns and currency appreciation rates. While these findings suggest that properly identifying and measuring global dynamics is essential for understanding international financial markets, none of these works is based on global implied volatility and its measurement, the exact goal of this work.

Are global risk dynamics simply driven by a spillover from US or a more sophisticated phenomenon? We address this question by constructing a global implied volatility measure and quantifying its relevance for international risk dynamics (implied and realized), expected equity returns around the globe, and investor behavior in foreign exchange markets.

Methodologically, our approach departs from the common practice of using simple market capitalization weighted averages of local implied volatilities. By estimating a dynamic factor model across international model-free implied volatility indices, we explicitly estimate a latent global shock that drives comovements in option-implied risk. This structure allows us to disentangle global from regional or idiosyncratic shocks, providing a cleaner measure of aggregate uncertainty as perceived by global investors.

The resulting Global Implied Volatility (GIV) index is a market-cap weighted average of estimted common components of international implied volatilities driven by the extracted global factor. Empirically, GIV isolates a source of global implied volatility risk not entirely spanned by the VIX or by local implied volatility indices, thus offering a truly international gauge of market fear. In practice, while the difference between GIV and VIX is by construction little, it spikes in coincidence with few important events, with GIV generally giving relatively more weight to global news as opposed to US news.

Our analysis is divided in three parts: 1) implied and realized volatilities, 2) equity premia, 3) currency portfolios. The main results are as follows.

1. GIV contains incremental predictive power beyond both the VIX and local implied volatility indices for forecasting implied and realized volatility. GIV outperforms the VIX and local measures across multiple dimensions. In daily out-of-sample forecasts, heterogeneous autoregressive (HAR) models (Corsi, 2009) augmented with GIV improve predictive accuracy for implied and realized volatilities across a wide range of international indices, with statistical significance in nearly all non-US markets. For implied volatility forecasts this is true in all non-US stock indices, one US index (Russell) and gold. The superiority of GIV for realized volatility indices holds even after controlling for a global realized volatility factor (Zhang et al., 2020) estimated, analogously to GIV, across a cross-section of international realized volatilities.[4]

[4] Zhang et al. (2020) show that global realized volatility enhances realized volatility forecasts around the globe.

2. We extend our framework to construct a global variance risk premium that outperforms the US VRP and local VRPs in forecasting excess stock returns around the world. It also outperforms the global VRP proposed by Bollerslev et al. (2014) providing new insights into the pricing of global jumps and tail risks. Our Global Variance Risk Premium ($GVRP$) is defined as the difference between GIV^2 and the expected global realized volatility. Unlike the global VRP of Bollerslev et al. (2014), which is based on the aggregation of local VRPs, our construction does not implicitly impose that implied and realized volatilities share identical global factor structures. This distinction is theoretically and empirically important. Under the risk-neutral measure, implied volatility embeds compensation for risks — such as large jumps and tail events — that investors fear but they may not materialize under the physical measure governing realized volatility. Consequently, assuming identical factor exposures across international implied volatilities and realized volatilities implicitly rules out that risk premia arise precisely from the differential pricing of jump and/or tail risks across different markets. Consistent with this mechanism, we find that the difference between our $GVRP$ and a global VRP in the spirit of Bollerslev et al. (2014) — obtained as cross-country VRP aggregation — closely tracks the evolution of global jumps.[5] This relationship echoes the empirical findings of Bollerslev and Todorov (2011, 2023) and Chong and Todorov (2024), who show that investors' sensitivity to rare and large market jumps — captured by implied volatilities under the risk-neutral measure — drives much of the variance risk premium's dynamics. By explicitly allowing for distinct loadings in international implied and realized volatilities, $GVRP$ isolates this globally priced component of jump risk.

   $GVRP$ robustly outperforms local, US, and the cross-country aggregated global VRP in predicting excess returns, with its additional predictive power emerging at medium to long horizons (8 to 20 months ahead).[6] This evidence complements the widespread result that the VRP only accounts for short-term predictability (Zhou, 2018) and resembles the medium to long horizon predictability of the emerging economies VRP documented by Qiao et al. (2024). The same conclusion is reached for different choices on the estimation of the VRPs and the forecasting equations. In fact, these results are qualitatively identical for expected realized volatilities obtained with HAR models or assuming random walk dynamics (as in Bollerslev et al., 2009), and using country-level predictive regressions or panel regressions (as in Bollerslev et al., 2014, and Qiao et al., 2024). In an out-of-sample exercise, $GVRP$ performs significantly better than the US VRP in predicting international stock returns.

3. We use variance risk premia to construct currency portfolios. We compare global VRPs and the US VRP using a strategy that goes long on the currencies of economies whose local VRP is above a reference global VRP, and short otherwise. In so doing, we follow the spirit of

[5] Global jumps are measured as market-cap-weighted average of local jumps which, in turn, are obtained as the gaps between local realized variances and local bipower variations.

[6] See Londono (2015) on the existence of US VRP spillovers which predict international stock returns.

Colacito et al. (2020) who propose a time series strategy based on output gaps differentials between national economies and the US. As compared with their strategy, by considering VRP gaps our currency portfolios are based on macroeconomic uncertainty rather actual macroeconomic conditions. Hence, underlying this strategy there is the expectation that economies subject to higher uncertainty (larger VRP than the reference global VRP) offer higher returns: such compensation makes investors willing to take long positions on the corresponding currencies. As reference global VRP we consider the US VRP, $GVRP$ and a global VRP based on Bollerslev et al. (2014)'s cross-country VRP aggregation. Unlike portfolios based on the gap with the US VRP, both global VRPs generate significant value for investors. Similarly to our evidence on international equity markets, $GVRP$ outperforms Bollerslev et al. (2014)'s global VRP by yielding larger expected returns and Sharpe ratio.

The rest of the paper is as follows. GIV measurement is described in Section 2. Section 3 presents forecasting results on international implied and realized volatilities. In Section 4 we study stock return predictability through the lenses of variance risk premia. In Section 5 we construct currency portfolios based on VRP gaps. Section 6 concludes.

2. Measuring Global Implied Volatility

Our international implied volatility dataset is obtained by collecting implied volatility indices which meet three criteria. First, in order to avoid reliance on strong assumptions on the pricing kernel, we only consider model-free measures.[7] Second, all implied volatility indices are 30-day expected realized volatility of an underlying index. Third, the indices are publicly and currently available with at least 15 years of historical daily data. For each market, we obtain data on option-implied volatility from various sources, which are shown in Panel A of Table 1 together with the names of the indices and the corresponding underlying stock market indices. Beyond stock market indices, two commodity indices meet our three criteria: gold and oil (Panel B of Table 1). As a result, our international implied volatility dataset consists of daily implied volatility indices for 14 international equity markets and 2 commodity markets. For simplicity, we consider a balanced panel. Since various indices have been launched on different dates, in order to study the same indices over time, we consider the period from April 1, 2010 to April 22, 2025.

Our global implied volatility measure is obtained in two stages.

1. *Common components of international implied volatilities.* The first step is dictated by an empirical regularity of implied volatility data: as evident in Figure 1, these measures display strong comovements. For example, the average pairwise correlation is 0.74. In order to account for this, we adopt a *generalized dynamic factor model* based on the

[7] See seminal works of Carr and Madan (1998), Britten-Jones and Neuberger (2000), Jiang and Tian (2005) on the motivation for model-free implied volatility and its development.

assumption that such comovements are generated by a set of common shocks. Letting IV_{it} be the ith implied volatility measure in our dataset, we assume

$$IV_{it} = \underbrace{\sum_{j=0}^{\infty} \mathbf{a}'_{ij}\mathbf{u}_{t-j}}_{\chi_{it}^{IV}} + e_{it}^{IV} \qquad\qquad i = 1, 2, \ldots, 16 \tag{1}$$

where $\mathbf{u}_t$ is a q-dimensional vector of implied volatility shocks common to all indices, $\mathbf{a}_{ij} = (a_{ij,1}, a_{ij,2} \ldots a_{ij,q})'$ is a vector collecting the effect at of each common shock after j days, χ_{it}^{IV} and e_{it}^{IV} denote the common (driven by common shocks) and idiosyncratic component of IV_{it} respectively. Unlike dynamic factor models of the "static" type (Stock and Watson, 2002; Bai and Ng, 2002), for which common factors are loaded only contemporaneously, generalized factor models introduced in the seminal work of Forni et al. (2000) do not impose any restriction on the international propagation of the common implied volatility shocks $\mathbf{u}_t$. Indeed, as argued by Hallin and Lippi (2013) generalized dynamic factor models arise as a representation result for large panels of comoving variables rather than modelling assumptions.

For the estimation of the generalized dynamic factor model we first need to determine the number q of common shocks in the data. Statistical methods, such as information criteria (Hallin and Liška, 2007) or testing procedures (Onatski, 2009) are available for that. These procedures indicate the presence of a single common implied volatility shock, that is, $q = 1$. This shock accounts for 80% of the total comovements across the implied volatilities in our sample; an additional shock would add a meagre 6%. For the rest, the estimation of (1) follows the generalized dynamic factor model estimator of Forni et al. (2005).

2. *Global Implied Volatility calculation.* Having identified the common components of our indicators, χ_{it}^{IV}, capturing the comovements in international implied volatilities, our global implied volatility measure, denoted GIV, is easily obtained in the second stage of our procedure by aggregation of common components. Restricting to equity implied volatilities, GIV is the market capitalization weighted average of common implied volatility components[8]

$$GIV_t = \sum_i w_{it}\hat{\chi}_{it}^{IV} \tag{2}$$

where w_{it} is the market capitalization of the ith market at time t measured in US dollars and $\hat{\chi}_{it}^{IV}$ the normalized estimate of χ_{it}^{IV} such that GIV has the mean and standard

[8] In the calculation of GIV, (2), we excluded RVX, KSVKOSPI and NIFVIX since their market capitalizations are not available in Datasteam over our full sample. However, these three indices are included in the estimation of the dynamic factor model in equation (1) because, as long as they support a factor structure, they help estimating the common implied volatility shock $\mathbf{u}$.

deviation of the cross-sectional average of our implied volatilities.[9]

The plot at the top of Figure 2 shows that the evolution of GIV in our sample is in line with the common interpretation of implied volatility. In fact, GIV spikes in correspondence of important negative events. While, by construction, this pattern is qualitatively similar to that of the VIX index, there is a regularity in the difference between GIV and VIX. As shown in the bottom plot of Figure 2, GIV tends to attach more (less) weight to events occurring out (in) the US. Positive realizations of the difference between VIX and GIV in excess of plus/minus 2 standard deviations (i.e. outside the band demarcated by thin solid lines) are related to episodes such as the EU sovereign debt crisis, concerns about global economic growth[10], the Brexit vote and the start of the war between Russia and Ukraine; large negative values correspond instead to a major US stock falls and Trumps' tariffs.

3. The predictive power of GIV for global risk

In this section, we conduct a comprehensive analysis of the empirical performance of GIV as a predictor of implied volatility and realized volatility. Our objective is to assess whether GIV contains incremental information about future volatility beyond that embedded in the VIX and local implied volatility indices. In order to avoid look-ahead bias, in this Section GIV is re-calculated at each time t using the dynamic factor model approach described in Section 2 but excluding observations dated $t+1$, $t+2$, and so on.

3.1. Forecasting implied volatilities

The question of forecasting the dynamics of implied volatility indices has long been studied (see e.g. Konstantinidi et al., 2008; Fernandes et al., 2014; Degiannakis et al., 2018, among others). Here, we assess the predictive content of GIV for future implied volatility in international equity markets.

To predict implied volatilities, we adopt augmented versions of the HAR model of Corsi (2009)[11]

$$iv_{i,t+1} = \beta_{i,0} + \beta_{i,1} iv_{i,t}^{(1)} + \beta_{i,5} iv_{i,t}^{(5)} + \beta_{i,22} iv_{i,t}^{(22)} + \gamma_{i,1} x_t^{(1)} + \gamma_{i,5} x_t^{(5)} + \gamma_{i,22} x_t^{(22)} + \varepsilon_{i,t+1} \tag{3}$$

[9] That is, we first standardize the IV_{it}'s and estimate their common components, say $\tilde{\chi}_{it}^{IV}$'s. Then we have

$$\hat{\chi}_{it}^{IV} = \frac{w_{it}}{\sum_i w_{it}} \bar{\sigma}^{IV} \tilde{\chi}_{it}^{IV} + \bar{IV}$$

where $\bar{IV} = (1/NT) \sum_t \sum_i IV_{it}$, $\bar{\sigma}^{IV} = \sqrt{\frac{1}{T-1} \sum_t \left(\bar{IV}_t - \bar{IV}\right)^2}$ and $\bar{IV}_t$ is the cross-sectional average implied volatility at time t.

[10] For this interpretation of February 12, 2016 events, see for example this article appeared on Reuters: reuters.com/article/world/whats-behind-the-global-stock-market-selloff-idUSKCN0VL0JB/.

[11] We model log-transformed implied volatility data as they are much closer to be normally distributed, and to avoid negativity issues.

where

- $iv_{i,t} = log(IV_{i,t})$;
- x_t is either $log\,(VIX_t)$ or $log\,(GIV_t)$;
- $z_t^{(k)} = k^{-1} \sum_{j=1}^{k} z_{t-j+1}$, for $z_t = iv_{i,t},\, x_t$, defines daily, weekly and monthly components (corresponding to $k = 1,\, 5,\, 22$ respectively) of $iv_{i,t}$ and x_t;

Accordingly, we consider three variants of (3):

- HAR the standard model obtained by setting $\gamma_{i,1} = \gamma_{i,5} = \gamma_{i,22} = 0$,

- HAR-VIX corresponding to $x_t = VIX_t$,

- HAR-GIV corresponding to $x_t = GIV_t$.

In all its variants, (3) is estimated in a rolling manner starting from a window that, out of approximately 15 years of daily trading data, contains the first 7 years of our sample, that is, the trading days between April 1, 2010 and March 31, 2017. Subsequent forecasts up to the last trading day in our sample are obtained using, at each time t, the most recent 7 years of trading data to estimate (3) and predict implied volatility at time $t+1$. Letting T_0 be the number of trading days in our initial window, we compute forecasts for $t = T_0,\, T_0+1,\, \ldots,\, T-1$, and measure the out-of-sample performance of the above models over a time span containing the trading days from April 1, 2017 until April 22, 2025.[12]

To measure forecast accuracy we use the mean-squared error (MSE) and average quasi-likelihood (QLIKE) loss functions

$$QLIKE_i = \frac{1}{T-T_0} \sum_{t=T_0+1}^{T} \left(\frac{iv_{i,t}}{\hat{iv}_{i,t}} - log\frac{iv_{i,t}}{\hat{iv}_{i,t}} - 1 \right) \tag{4}$$

$$MSE_i = \frac{1}{T-T_0} \sum_{t=T_0+1}^{T} \left(iv_{i,t} - \hat{iv}_{i,t} \right)^2 \tag{5}$$

where $\hat{iv}_{i,t}$ is the prediction based on one of the three forecasting models. As established by Patton (2011), MSE and QLIKE are the only loss functions robust to the unavoidable noise in the volatility proxies. Letting $\mathcal{L}_i\,(a)$ be either $QLIKE_i$ or MSE_i obtained with the predictive model a, in the rest of this Section we report relative losses $Rel\text{-}\mathcal{L}_i\,(a/b) = \mathcal{L}_i\,(a)\,/\mathcal{L}_i\,(b)$ between a's and b's predictions.

Table 2 presents the out-of-sample forecast evaluation of the HAR-type models for implied volatility, where the baseline HAR specification is augmented either with the Global Implied Volatility (GIV) index or with the US VIX. We report the relative (MSE and $QLIKE$) losses

[12]Given the differences in trading days across countries, we only retain common trading days. When a day is discarded returns are computed at a 2-day horizon (or more if there are more than two consecutive trading days which are not common across all markets).

for the GIV-augmented HAR model with respect to (i) the benchmark HAR model (GIV/bnc) and (ii) the HAR model augmented with VIX (GIV/VIX). Values below one indicate superior predictive performance of the GIV-augmented model, while values above one imply inferior accuracy. The statistical significance of differences in forecast performance is assessed using the test of Giacomini and White (2006). The results indicate that incorporating GIV substantially enhances volatility forecasts across both equity and commodity markets. Relative to the baseline HAR model, the GIV/bnc ratios are consistently and significantly below one for both MSE and $QLIKE$ loss functions. The largest improvements are observed for European indices ($VDAX$, $VSTOXX$, $IVUKX30$, and $VSMI$), where the inclusion of GIV reduces forecast errors by more than half, suggesting that these markets are particularly sensitive to global volatility dynamics. When compared to the HAR model augmented with VIX (GIV/VIX), the GIV-augmented specification continues to outperform in the majority of cases. The relative losses remain below unity and statistically significant at 1% level for all markets outside the US (VIX outperforms GIV for the two US euity indices, VXD and VXN, and oil, OVX). This finding indicates that the predictive information embedded in GIV extends beyond that captured by VIX, reinforcing its role as a more comprehensive measure of global risk.

The empirical findings reported in Table 2 are based on the logarithmic transformation of implied volatility. This choice is motivated by the well-known distributional properties of implied volatility, which typically exhibits pronounced right-skewness and fat tails. By contrast, log-implied volatility is much closer to Gaussian, as documented in Table A.1 of the Appendix, making it more amenable to linear forecasting frameworks such as the HAR model. This practice is well-established in the realized volatility literature; for instance, Andersen et al. (2003) observe that the distribution of logarithmic realized volatility is much closer to normal, and Andersen et al. (2007) find that HAR models perform robustly whether using realized variance, realized volatility, or their logarithms. In the context of implied volatility, Fernandes et al. (2014) also adopt $\log(IV)$ for their modeling approach. However, the ultimate objective is the ability to forecast the level of implied volatility. To this end, Table A.2 of the Appendix reports out-of-sample forecast evaluations for HAR models estimated directly on the level of implied volatility. The results are qualitatively consistent with those obtained using the logarithmic series, confirming that the predictive superiority of our global measures remains robust regardless of the chosen scale.

All in all, these results underscore the relevance of global information flows in shaping expectations of future volatility and demonstrate the value of incorporating cross-market implied volatility linkages into predictive modeling frameworks.

3.2. Forecasting realized volatilities

We now examine whether GIV predicts realized volatility. Implied volatility indices have long been recognized as valuable forward-looking measures for predicting future realized volatility. Early studies such as Christensen and Prabhala (1998), Blair et al. (2001), and Poon and

Granger (2003) document that implied volatility generally outperforms historical volatility and GARCH-type models (based on daily volatility proxies) because it reflects risk-neutral expectations extracted from option prices. The introduction of model-free implied volatility further strengthened this link (Jiang and Tian, 2005).

At the same time, the availability of high-frequency data has enabled a deeper understanding of volatility. Andersen and Bollerslev (1998) were the first to model and forecast realized volatility based on the summation of high-frequency intraday squared returns. Realized volatility offers a far more accurate proxy for true return volatility because it is constructed from high-frequency intraday data. Therefore, unlike daily squared returns (or range-based measures), intraday proxies allow the econometrician to capture the latent integrated variance. As demonstrated by Andersen and Bollerslev (1998), while daily squared returns are unbiased estimators, they are extremely noisy. In contrast, realized volatility converges to the true integrated volatility (the actual cumulative variance over a period) as the sampling frequency increases, allowing to use standard time-series models with significantly higher predictive accuracy.

Due to its simplicity and ability to reproduce volatility persistence, the Heterogeneous Autoregressive (HAR) model proposed by Corsi (2009) has become the most popular model in volatility forecasting. Using the HAR model, Busch et al. (2011) show that implied volatility is a strong predictor of realized volatility.[13] Bekaert et al. (2025) evaluate 320 forecasting models for monthly stock-return volatility across international equity markets and find that a logarithmically transformed HAR model, when augmented with option-implied volatility, consistently ranks among the best-performing volatility forecasts across both countries and time periods.

Existing research on the predictive power of implied volatility has primarily examined the role of local implied volatility indices to forecast domestic realized volatility, or has focused on spillover effects from the US VIX to international markets. Buncic and Gisler (2016) and Liang et al. (2022) show that US equity market volatility information improves realized volatility forecasts in a large-cross section of international equity markets. Motivated by the strong links in international financial markets, Zhang et al. (2020) construct a global realized volatility measure to incorporate the cross-national volatility flows into the individual realized volatility forecasting. They find that global realized volatility enhances realized volatility forecasts around the globe. By taking global risk into account, we clearly follow a similar spirit, however we examine global implied volatility rather than realized, hence extending their evidence. In fact, in what follows we analyze whether global implied volatility contains predictive power which is not subsumed by global realized volatility.

Our dataset consists of daily realized variances indices for 28 international equity markets. We consider the period from April 1, 2010 to June 22, 2022.[14] Following the seminal work of Andersen et al. (2003), daily realized variance is defined as the summation of the intraday

[13] See also Kambouroudis et al. (2021) who demonstrate that implied volatility indices yield substantial gains in both statistical and economic forecasting accuracy across global equity markets.

[14] The last observation available in the Oxford-Man Realized library dataset is indeed dated June 22, 2022.

squared returns,

$$RV_{i,t} = \sum_{j=1}^{M} r_{i,t,j}^2 \tag{6}$$

where $M = 1/\Delta$, Δ is the commonly adopted 5-minute sampling frequency, and $r_{i,t,j}$ refers to the log intraday return observed on the jth intraday interval of day t in the ith market. We use daily international realized variances based on 5-minute intraday returns taken from the Oxford-Man Institute's Realized Library Heber et al. (2009). As shown by Liu et al. (2015), the estimator based on 5-minute interval robustly outperforms a wide variety of alternatives. Table 3 provides the names of the realized variance indices and the corresponding stock index.

Similarly to implied volatility predictions, for realized variances we also adopt augmented HAR models

$$\begin{aligned} rv_{i,t+1} = \beta_{i,0} + \beta_{i,1} rv_{i,t}^{(1)} + \beta_{i,5} rv_{i,t}^{(5)} + \beta_{i,22} rv_{i,t}^{(22)} + \gamma_{i,1} x_t^{(1)} + \gamma_{i,5} x_t^{(5)} + \gamma_{i,22} x_t^{(22)} + \\ + \delta_{i,1} grv_t^{(1)} + \delta_{i,5} grv_t^{(5)} + \delta_{i,22} grv_t^{(22)} + \varepsilon_{i,t+1} \end{aligned} \tag{7}$$

where

- $rv_{i,t} = log(RV_{i,t})$;
- x_t is either $log\left(VIX_t^2\right)$ or $log\left(GIV_t^2\right)$;
- $z_t^{(k)} = k^{-1} \sum_{j=1}^{k} z_{t-j+1}$ for $z_t = rv_{i,t}$, x_t defines daily, weekly and monthly components (corresponding to $k = 1$, 5, 22 respectively) of $iv_{i,t}$ and x_t;
- $grv_t = log(GRV_t)$, where GRV_t is the global realized variance calculated as described below.

Accordingly, we consider five variants of (7):

- HAR the standard model obtained by setting $\gamma_{i,1} = \gamma_{i,5} = \gamma_{i,22} = \delta_{i,1} = \delta_{i,5} = \delta_{i,22} = 0$,

- HAR-VIX corresponding to $x_t = log\left(VIX_t^2\right)$ and $\delta_{i,1} = \delta_{i,5} = \delta_{i,22} = 0$,

- HAR-GIV corresponding to $x_t = log\left(GIV_t^2\right)$ and $\delta_{i,1} = \delta_{i,5} = \delta_{i,22} = 0$,

- HAR-VIX&GRV corresponding to $x_t = log\left(VIX_t^2\right)$,

- HAR-GIV&GRV corresponding to $x_t = log\left(GIV_t^2\right)$.

Motivated by the main conclusions of Zhang et al. (2020) that a HAR model augmented with global realized volatility and VIX provides the most accurate realized volatility forecasts, we construct GRV in a similar manner as GIV. Specifically, we obtain a GRV measure as follows:

$$RV_{it} = \underbrace{\sum_{j=0}^{\infty} \mathbf{b}'_{ij} \mathbf{v}_{t-j}}_{\chi_{it}^{RV}} + e_{it}^{RV} \qquad\qquad i = 1, 2, \ldots, 28 \tag{8}$$

$$GRV_t = \sum_i w_{it} \hat{\chi}_{it}^{RV} \tag{9}$$

where $\mathbf{v}_t$ is a vector of common realized variance shocks, $\mathbf{b}_{ij}$ is the the vector of coefficients collecting the effect on RV_{it} of of each common realized variance shock occurred at time $t-j$, and χ_{it}^{RV} is common component of RV_{it} driven by $\mathbf{v}_t$. Once we detect one common shock in realized variances, GRV is obtained analogously to GIV in equation (2) as a USD market-capitalization weighted average of normalized estimates of realized variances' common components.[15] Such common realized variance shock accounts for 60% of the total comovements among the realized variances in our sample; a second shock would increase the ratio by 7%.[16]

We assess out-of-sample models' performances in predicting realized variances similarly to the case of implied volatility in Section 3.1. In all its variants, (7) is estimated in a rolling manner starting from a window that contains the trading days between April 1, 2010 and March 31, 2017 as the one used for implied volatility. We evaluate the out-of-sample performance of the models over a time span containing the trading days from April 1, 2017 until June 22, 2022 using the MSE and QLIKE functions.

Table 4 reports the out-of-sample performance of alternative HAR-type models in forecasting realized variance across a broad set of international equity markets. The table presents relative forecast loss for (i) a HAR model augmented with GIV with respect to the baseline HAR model (GIV/bnc), (ii) the GIV-augmented HAR relatively to a VIX-augmented HAR (GIV/VIX), and (iii) a HAR model incorporating both GIV and GRV relative to one combining VIX and GRV ($GIV\&GRV/VIX\&GRV$). Ratios below unity indicate that the numerator model, which includes GIV, provides more accurate forecasts than the denominator which excludes GIV. The test of Giacomini and White (2006) is employed to assess the statistical significance of differences in forecast performance.

The results reveal three key findings. First, augmenting the HAR model with GIV significantly enhances predictive accuracy relative to the benchmark HAR model across all markets. The GIV/bnc ratios are consistently below one and highly significant for both loss measures (MSE and QLIKE). This means that GIV contains substantial incremental information about

[15]In the GRV calculation of (9) we excluded Russell, KS11, NSEI since their market capitalizations are not available in Datasteam over our full sample. However, these three indices are included in the estimation of the dynamic factor model in equation (8) because, as long as they support a factor structure, they help estimating the common realized volatility shock $\mathbf{v}$.

[16]Alternative to principal component methods and factor models, Zhang et al. (2020) also consider a cross-sectional average estimation of GRV. All results in this section are very similar using the latter estimator of GRV. This evidence, unreported here, is available upon request.

future realized variance beyond that embedded in lagged realized volatility components alone.

Second, when compared with the HAR-VIX specification (GIV/VIX), the GIV-augmented model generally maintains superior forecasting performance across most non-US equity markets. Ratios below one for the majority of European and Asia-Pacific indices suggest that GIV captures global volatility dynamics extending beyond the information content of US implied volatility. For US markets (S&P 500, Dow Jones, NASDAQ, Russell 2000), however, the GIV/VIX ratios exceed one, consistent with the notion that the VIX remains the dominant driver of realized variance within the United States.

Third, when we control for GRV (case *iii*), GIV continues to outperform to VIX. Although the addition of GRV modestly reduces the relative gains from GIV in some markets, the $GIV\&GRV/VIX\&GRV$ ratios remain below unity and statistically significant for most developed and several emerging markets. This finding indicates that GIV provides complementary predictive information to GRV, rather than overlapping with it, reinforcing the interpretation that global implied volatility reflects expectations about future risk that are not fully captured by realized volatility measures.

In Table 4, the GRV is estimated using a factor model. An alternative approach, proposed by Zhang et al. (2020), consists of estimating GRV as a simple cross-sectional average of local realized variances. The results for this specification are reported in Table A.3 of the Appendix. Consistent with our main findings, the results are very similar when using this alternative estimator of GRV, indicating that our conclusions are robust to the method used to construct global realized variance.

In addition, similar to the evaluation conducted in Section 3.1 where we assessed the models' ability to forecast the level of implied volatility, we perform a corresponding check for realized volatility. In Table A.4 of the Appendix, we report the out-of-sample forecasting results for realized volatility in levels rather than in logarithms. The results are qualitatively unchanged: HAR models augmented with GIV continue to outperform both the benchmark HAR specification and the corresponding VIX-based models across most markets. This confirms that the predictive gains associated with global implied volatility extend to forecasting realized volatility in levels and are not driven by the log transformation.

Overall, these results demonstrate that the GIV factor constitutes a powerful global predictor of future realized variance, offering incremental forecasting gains over both traditional domestic volatility and US volatility.

4. A global variance risk premium

A large literature shows that the variance risk premium (VRP) – defined as the difference between risk-neutral and physical expectations of future variance – can be used as proxy for the economic uncertainty (Drechsler and Yaron, 2011; Drechsler, 2013). In their seminal work, Bollerslev et al. (2009) demonstrate that the VRP effectively captures time-varying risk aversion and macroeconomic uncertainty, serving as a robust predictor of aggregate US stock market returns, particularly at short horizons. More recently, Londono and Xu (2023) provide empirical evidence for the ability of US upside and downside VRP to predict international stock returns.

Given the integrated nature of financial markets, recent literature has extended this framework beyond the US to a global context. Bollerslev et al. (2014) provide comprehensive international evidence, showing that a "global" VRP, constructed as a market-capitalization-weighted average of local variance risk premia, holds significant predictive power for returns across distinct national markets. This predictability extends to other asset classes as well. Londono and Zhou (2017) demonstrate that global variance risk premia can explain variations in currency markets and forecast foreign exchange returns. More recently, Qiao et al. (2024) highlight the relevance of VRPs in emerging markets, finding predictability at medium-to-long horizons that contrasts with the short-run predictability typically observed in developed markets.

In this section, we use the GIV and GRV constructed in the previous sections to obtain a global variance risk premium. Such global VRP is then used in the next subsections to predict excess equity returns, and in Section 5 to construct currency portfolios. These exercises are motivated by a vast body of literature on the variance risk premium, which is discussed later on.

The VRP is defined as the difference between the expected variance under the risk-neutral probability measure $\mathbb{Q}$ and the physical probability measure $\mathbb{P}$. In practice, the widespread empirical measure for monthly VRP takes implied variance indices for options with 30 days to maturity as risk-neutral expectations and expected realized variance 30 days ahead. That is, the VRP in the ith market in month t is

$$VRP_{it} = IV_{i,t}^2 - E_t(RV_{i,t+1}) \tag{10}$$

where $IV_{i,t}^2$ is the risk-neutral expectations of the future return variations, or the option-implied variance, and $E_t(RV_{i,t+1})$ is the statistical expectations of the future return variations. $E_t(RV_{i,t+1})$ is a realized variance forecast. Since we refer to monthly observations, in this section we need to redefine our indicators as follows.

$IV_{i,t}$ denotes the monthly implied volatility in the ith market obtained as the end of the month t daily observation in the corresponding market.

$RV_{i,t}$ is the monthly realized variance in the ith market obtained by aggregating daily realized variances within month t.[17]

These choices are widespread in this literature, see e.g. Zhou (2018) and references therein.

[17]Recalling that the number of trading days per month varies according to the number of common trading days across all markets, we need to normalize monthly realized variances otherwise they would be artificially lower in months with fewer trading days. Letting $\mathcal{T}_t$ the number of common trading days in month t, the corresponding monthly realized variance in the ith market in month t is the weighted average of the daily realized variances $22/\mathcal{T}_t \sum_{\tau}^{\mathcal{T}_t} RV_{i,\tau}$.

We construct the global variance risk premium (GVRP) as the difference between the GIV^2 and GRV introduced in Section 2 and 3.2, respectively.

$$GVRP_t = GIV_t^2 - E_t(GRV_{t+1}) \tag{11}$$

4.1. Does $GVRP$ contain new information on equity premia around the world?

Our dataset consists of the same 28 stock market indices used in Section 3.2. For the return data, we download the close prices of these indices from Datastream.[18] The risk-free measure for calculating excess returns is the 3-month Treasury bill.

To examine the predictive power of our $GVRP$ for stock index excess returns we use the predictive regression

$$\hat{rx}_{i,t+h|t} = \hat{a}_h^i + \hat{b}_h^i GVRP_t + \hat{c}_h^i X_t \tag{12}$$

where $\hat{rx}_{i,t+h|t}$ refers to the h-step ahead prediction of the monthly excess stock return for the ith market, X_t is either the US VRP ($VRP_{US,t} = IV_{US,t}^2 - E_t(RV_{US,t+1})$) or the local VRP of the ith market. In our dataset, we have 11 local VRPs corresponding to the number of implied volatility indices in our sample.

We now discuss the estimates for b_h^i and their significance, based on Newey-West t-statistics, for $h = 1$, 6, 12, 18, 24. In Table 5 we refer to the case in which we do not control for the US or local VRP (i.e. $c_h^i = 0$). The results show that these coefficients are negative and insignificant at the shortest one-month horizon. However, as the horizon extends, the coefficients increase sharply, reaching their largest and most significant values around the 12- to 18-month horizons, before gradually declining at longer horizons. The results in Table 6 indicate that the $GVRP$ has meaningful predictive power for future excess stock returns even after controlling for the US VRP or the local VRP. Specifically, the estimated b_h^i's are generally insignificant or small at the one-month horizon, but become positive and statistically significant at medium to longer horizons (6 to 24 months) for most markets. This pattern suggests that the impact of global variance risk on expected returns builds over time reflecting a gradual incorporation of global volatility information into market pricing. All in all, these results confirm the role of $GVRP$ as a distinct global risk factor influencing equity return predictability beyond national or US-specific volatility dynamics.

Tables 7 and 8 replicate the predictive return analysis of Tables 5 and 6, but now using a random-walk assumption for realized variance (as in Bollerslev et al. (2009) and subsequesnt works) when constructing the global, US, and local variance risk premia, instead of relying on HAR-based forecasts as in the earlier tables. Despite this change in the expectation model for realized variance, the results remain broadly consistent. In Table 7, where no additional controls are included, the estimated b_h^i coefficients continue to be negative or insignificant at the one-

[18] We consider the same period as in Section 3.2, from April 1, 2010 to June 22, 2022, which is the last available observation in the Oxford-Man realized library.

month horizon and become increasingly positive and statistically significant at medium horizons, before moderating at longer horizons. Table 8 shows that the predictive power of the $GVRP$ also persists after controlling for either the US or local VRP. Overall, these results reinforce the robustness of the $GVRP$ as a predictor of future excess returns.

Following Bollerslev et al. (2014), we now force VRPs predictive regression coefficients to be the same across all equity markets. Table 9 reports the panel regression estimates obtained from

$$\hat{rx}_{i,t+h|t} = \hat{a}_h + \hat{b}_h GVRP_t + \hat{c}_h X_t \tag{13}$$

In the table we evaluate the predictive role of the $GVRP$ in a panel setting using two alternative methods for forming expectations of realized variance: (i) HAR-based forecasts and (ii) a simple random-walk (RW) assumption. Panel A presents results without additional controls (i.e. $\hat{c}_h = 0$), Panel B conditions on the US VRP, and Panel C includes the country-specific VRP.

Across all specifications, the results show a consistent pattern. The coefficient on the $GVRP$ is negative and insignificant at the one-month horizon but becomes positive and statistically significant from 6 to 24 months. These medium- and longer-horizon coefficients remain robust even when controlling for either the US VRP (Panel B) or local VRP (Panel C), indicating that the $GVRP$ retains independent predictive power beyond national or US-specific volatility risk. The HAR-based GVRP generally produces slightly larger coefficients than the RW-based version, though both approaches deliver qualitatively similar results. Overall, the panel regressions confirm that global variance risk commands a significant return premium that strengthens with the forecasting horizon and is not subsumed by domestic or US variance risk premia.

4.2. $GVRP$ vs US VRP, local VRPs and their aggregation

In the previous section, we documented that $GVRP$ contains predictive information for international excess stock returns beyond that in the US VRP or local VRPs. However, ours is not the first work proposing a global VRP. Bollerslev et al. (2014) suggest a market capitalization weighted average of local variance risk premia, that is

$$GVRP_t^a = \sum_i w_{it} VRP_{i,t+1} \tag{14}$$

We denote this measure as $GVRP^a$ to stress cross-country VRP aggregation as opposed to our global approach to the VRP which is based on separate aggregations of international implied volatilities and realized volatilities. It is straightforward to show that there is a special case in which our measure coincides with theirs (i.e. $GVRP_t = GVRP_t^a$). This is the case if $\sum_i w_{it} \left(\hat{e}_{it}^{IV} - \hat{e}_{it}^{RV}\right) = 0$, that is the common factor structure across international implied volatilities is same to that across the corresponding realized volatilities.

Similarly to $GVRP^a$, we consider another measure based on the aggregation of local VRPs but using a dynamic factor model, that is

$$VRP_{it} = \underbrace{\sum_{j=0}^{\infty} \mathbf{c}'_{ij}\mathbf{z}_{t-j}}_{\chi_{it}^{VRP}} + e_{it}^{VRP} \qquad i = 1, 2, \ldots, n_{VRP} \tag{15}$$

$$GVRP_t^f = \sum_i w_{it}\hat{\chi}_{it}^{VRP} \tag{16}$$

which we denoted as $GVRP_t^f$ to stress that the cross-country VRP aggregation is obtained using a factor model.[19] $GVRP^f$ reverts to $GVRP^a$ if $\sum_i w_{it}\hat{e}_{it}^{VRP} = 0$, that is the market-cap weighted average is the best possible aggregation of international VRPs in mean-square error terms.

As in our sample we have the USD market capitalization of 11 equity markets for which we also have an implied volatility index, $GVRP^a$ and $GVRP^f$ are calculated using 11 local variance risk premia.

We compare the performance of our $GVRP$ measure to predict excess stock returns with respect to the US VRP, local VRP, $GVRP_t^a$ and $GVRP_t^f$ using the R_{OS}^2

$$R_{OS}^2\,(b) = 1 - \frac{MSE_{GVRP}}{MSE_b} \tag{17}$$

where b denotes either the US VRP or the local VRP, or one of the two global VRPs based on cross-country aggregation of local VRPs ($GVRP^a$ and $GVRP^f$). Figures 3 and 4 report the average out-of-sample R_{OS}^2 gains (in coordinate) per horizon $h = 1, 2, \ldots, 24$ (in abscissa) across the 28 international equity markets.[20] The top panels present results from individual country-by-country predictive regressions, while the bottom panels present the corresponding gains based on panel regressions, which exploit cross-sectional information.

Figure 3 is based on HAR-model expectations of realized variance, while Figure 4 repeats the exercise assuming that realized variance follows a random walk. Across both figures, the overall pattern is similar: our $GVRP$ systematically improves the predictive performance across forecast horizons following a pattern which is qualitatively similar no matter whether $GVRP$ is compared against the US VRP, local VRPs, $GVRP^a$ or $GVRP^f$. The gains are modest at short horizons but increase steadily up to around 18-20 months. Specifically, the US VRP tends to perform slightly better up to around the 7-month horizon. However, from horizon 8 onward the $GVRP$ systematically improves predictive performance reaching an average R_{OS}^2 improvement in excess of 3% relative to the US VRPs. A similar pattern is observed when comparing $GVRP$ with the local VRPs. Local VRPs appear to perform relatively better at very

[19] As in GIV and GRV estimation, we adopt a dynamic factor model driven by a single shock. Such common VRP shock accounts for 88% of the comovements across the local VRPs in our sample.

[20] When comparing the performance of $GVRP$ with respect to the local VRP, the reported average out-of-sample R_{OS}^2 gains are computed only for the subset of markets for which an implied volatility index is available.

short horizons, roughly up to 3–4 months, but from horizon 5 onward the GVRP consistently provides superior predictive accuracy. When comparing the alternative global measures, the $GVRP$ always outperforms $GVRP^a$ in the individual country-by-country predictive regressions reaching an average R^2_{OS} improvement of about 3% . In the panel regressions, the superiority of $GVRP$ becomes more evident from approximately horizon 8 onward. Finally, when compared with $GVRP^f$, the latter shows slightly stronger predictive performance at very short horizons (up to about 3 months), while from horizon 4 onward the $GVRP$ again systematically dominates reaching an average R^2_{OS} improvement in excess of 5%. Taken together, these findings highlight the enhanced informational content of the proposed GVRP in capturing the global component of variance risk relevant for future equity returns.

We now assess whether the superior in-sample performance of $GVRP$ also holds out-of-sample. Because the available sample is relatively short — comprising only 147 monthly observations — we assess the forecasting performance of $GVRP$ based on panel regressions, and assuming that realized variances follow a random walk rather than a HAR model. This approach allows us to minimize the loss of observations for the estimation of the forecasting models and thus retain as much data as possible for the out-of-sample forecast evaluation. For the same reason, forecasts are calculated only up to the six-month forecast horizon. In Table 10 we report mean-square error gains according to the R^2_{OS} (HA) statistics, where HA denotes the widespread historical average benchmark (Campbell and Thompson, 2008) for which returns are unpredictable beyond their unconditional average (or equivalently prices follow a random walk plus drift). Entries in bold indicate that the R^2_{OS} (HA) in Panel A (Panel B) is positive, significant and larger than the corresponding R^2_{OS} (HA) reported in Panel B (Panel A). This evidence strongly favors $GVRP$. As demonstrated in Panel A, $GVRP$ yields positive and statistically significant R^2_{OS} values for the vast majority of the indices, with its performance frequently surpassing that of the US VRP (in Panel B), as indicated by the high concentration of bold entries. Remarkably, $GVRP$ demonstrates stronger predictive power even within the domestic US markets – including the S&P 500 and Dow Jones Industrial Average – relative to the US VRP across nearly every horizon. The cross-market averages in Panel C further underscore the relative dominance and stability of the GVRP as a forecasting tool compared to the traditional US benchmark. While the US VRP exhibits a sharp decay in predictive accuracy from 3-month horizon onwards — often yielding negative average R^2_{OS} values between months three and five — $GVRP$ maintains consistently positive and statistically significant averages throughout the forecast window. The reported ΔR^2_{OS} values, which peak at the three-month horizon with a margin of 4.612%, confirm that the global measure incorporates unique, non-redundant information that is not fully reflected in US market sentiment alone.[21]

[21] In unreported results, we find that $GVRP$ always outperforms the alternative global measures, $GVRP^a$ and $GVRP^f$.

4.3. Understanding the global variance risk premium: jumps

Since $GVRP$ outperforms both $GVRP^a$ and $GVRP^f$, we have established the superiority of a direct, global measure of variance risk premium rather than cross-country aggregation. Therefore, implied volatilities and realized volatilities obey different factor structures when international indices are aggregated. To provide an economic explanation to this empirical result, we need to find a component of priced risk which differs across $\mathbb{P}$ and $\mathbb{Q}$. Bollerslev et al. (2011) identify such component as the perceived risk of large jumps. Based on the crucial distinction between actual and perceived jump risk, their Investors Fears index is based on priced jump risk which, unlike previous works, does not depend on the actual probabilities. More recent works incorporate similar mechanisms for which jumps drive a wedge between risk-neutral and actual measures. For example, Chong and Todorov (2024) allow the law of large jumps to differ under $\mathbb{P}$ and $\mathbb{Q}$, unlike the dynamics of diffusive volatility and small, frequent jumps, which instead coincide under $\mathbb{P}$ and $\mathbb{Q}$.

Is the superior performance of our $GVRP$ compared to the $GVRP_t^a$ due to the international price of jump risk? To answer this question, we compare the difference between the two global VRP measures, $\Delta GVRP_t \equiv GVRP_t - GVRP_t^a$, with a measure of global jumps J_t, obtained as the market-cap weighted average $J_t = \sum_{i=1}^{n_{IV}} w_{it} J_{it}$, where J_{it} is a standard measure of local jumps based on the difference between realized variance and bipower variance in the ith market. After standardization, Figure 5 shows a remarkably similar pattern in these quantities. More quantitatively, the projection of $\Delta GVRP_t$ onto J_t (including a constant) yields an R^2 equal to 0.69 and 1-percent significant estimates, with a positive slope coefficient. We conclude that, in line with the above works, our $GVRP$ measure indeed reflects investors' perception of international jump risk.

5. Variance risk premia and currency portfolios

We now investigate whether global VRP measures can be exploited by investors in FX markets. Londono and Zhou (2017) demonstrate that the US equity-VRP and a global currency VRP predict currency appreciation rates. We focus on currency portfolios and test the working hypothesis that the position of a market's VRP relatively to a reference global VRP is any useful to investors in FX markets. If yes, a positive (negative) gap between the local VRP and a global VRP measure indicates positive (negative) expected returns on the corresponding currency. This rationale suggests a strategy which takes long positions on positive VRP gaps (local minus global) and short positions on negative VRP gaps. Such strategy is very close in spirit with the time series strategy of Colacito et al. (2020), which is based on output gaps differentials between local economies and the US. In fact, like them we construct currency portfolios by distinguishing between strong and weak economies and taking the perspective of investors who buy currencies of strong economies and sell those of weak economies. However, instead of using actual macroeconomic data (output gaps), we rely on the ability of variance risk premia to reflect economic uncertainty, and so determine macroeconomic outcomes.

We consider currencies in the economies for which we have a local VRP measure: Japanese Yen (JPY), Australian Dollar (AUD), Indian Rupee (INR), South Korean won (KRW), Euro (EUR), Pound Stirling (GBP), Swiss Franc (CHF). Currency excess returns are as follows. For these currencies we take daily mid spot and forward rates with respect to the US dollar. The excess return obtained by an investor who buys the generic ith currency in the forward market at time t and sells it in the spot market at time $t+1$ is

$$rx_{i,t+1} = \frac{S_{i,t+1} - F_{i,t}}{S_{i,t}} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} - \frac{F_{i,t} - S_{i,t}}{S_{i,t}} \tag{18}$$

where $S_{i,t}$ and $F_{i,t}$ denote time t spot and forward price in USD of the ith currency. In order to understand whether any predictability in excess currency returns comes from spot rate dynamics rater than nominal interest rate levels, we use the approximation forward premium approximation $\frac{F_{i,t}-S_{i,t}}{S_{i,t}} \approx \iota_{i,t} - \iota_t^*$, where $\iota_{i,t} - \iota_t^*$ denotes the nominal interest rate differential between the ith country and the US, which holds under the covered interest parity. In practice, this approximation allows us to disentangle expected portfolio returns from those of carry strategies which are entirely driven by interest rate differentials.

The portfolios are as follows. At the end of each month, we consider equally weighted time series portfolios taking long (short) positions on currencies of countries whose equity market VRP is above (below) a reference VRP. As reference VRP we consider the US VRP, our $GVRP$, and $GVRP^a$.

The first result standing out from Table 11 is that the US VRP generates virtually no return. While, both global VRP measures are associated with significant compensation for investors, the evidence seems stronger for $GVRP$ rather than that $GVRP^a$. In fact, as compared with the global VRP obtained as in Bollerslev et al. (2014) via aggregation of local VRPs, our $GVRP$ measure yields a Sharpe ratio of 0.62 instead of 0.44 and a positive return which is 5%- rather than 10%-significant using Newey and West (1987) standard errors. As seen in the row denoted by "Irdiff", this economic value is not associated with interest rate differentials or violations of the covered interest parity: when we isolate the forward premium component of currency returns we find negative expected returns. This means that, portfolio based on VRP gaps between global and local VRPs generate returns by capturing spot exchange rate predicability, rather than interest rate differentials as in carry strategies. $GVRP$ gives a somewhat lower turnover than both the US VRP and $GVRP^a$ (see the row denoted by "TO"). In Figure 6 we plot the cumulative excess returns in the three portfolios. The shaded area corresponds to COVID recession dates in the US, whose onset coincides with persistent losses in all three portfolios. In the first part of the sample up to approximately the end of 2014 the two global measures ($GVRP$ and $GVRP^a$) display a very similar performance. The superior performance of $GVRP$ with respect to $GVRP^a$ is mostly due to the next couple of years and persists afterwards.

6. Conlusions

We construct a simple measure of global implied volatility (GIV) based on a dynamic factor model and model-free implied volatilities. Our empirical analysis shows that GIV captures aspects of global uncertainty that are not fully reflected in the VIX and local implied volatilities.

Building on GIV, we construct a global variance risk premium (GVRP) which unlike, its counterpart based on a cross-country VRP aggregation (Bollerslev et al., 2014), captures global jump risk. Thanks to this, our GVRP displays incremental predictive power for stock returns around the world and generates superior currency portfolios.

It is known that implied volatility is key to understanding macro-financial linkages. For example, Faccini et al. (2019) propose an option-based measure of risk aversion with predictive power for the real economic activity. Beyond the scope of this paper, GIV is likely to provide similar results at an international scale. Also high in our research agenda is an international approach to flight to safety dynamics based on GIV.

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Tables

Table 1: Implied volatility data

Market	IV	Underlying index	Source
		Panel A: equity markets	
United States	VIX	S&P 500	Datastream
United States	VXD	Dow-Jones	Datastream
United States	VXN	Nasdaq 100	Datastream
United States	RVX	Russell 2000	Datastream
United Kingdom	IVUKX30	FTSE 100	FTSE
Italy	IVMIB30	FTSE MIB	FTSE
Germany	VDAX	DAX 30	Datastream
Switzerland	VSMI	SMI 20	Datastream
Euro area	VSTOXX	STOXX 50	Datastream
Hong Kong	VHSI	Hang Seng	Datastream
Japan	JNIV	Nikkei 225	Datastream
South Korea	KSVKOSPI	KOSPI 200	Datastream
India	NIFVIX	Nifty 50	Datastream
Australia	AVIX	S&P/ASX 200	FactSet
		Panel B: commodity markets	
Gold	GVZ	SPDR Gold Shares	Datastream
Oil	OVX	United States Oil Fund	Datastream

Table 2: Oos IV forecasts: relative MSE and QLIKE losses

	Rel-MSE(·)		*Rel*-QLIKE(·)	
	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$
VIX	**0.889*****		**0.889*****	
VXD	**0.714*****	1.209***	**0.680*****	1.197*
VXN	**0.906*****	1.096***	**0.909*****	1.098***
RVX	**0.933*****	**0.959*****	**0.930*****	**0.960*****
IVUKX30	**0.358*****	**0.587*****	**0.361*****	**0.595*****
IVMIB30	**0.718*****	**0.898*****	**0.742*****	**0.913*****
VDAX	**0.365*****	**0.581*****	**0.371*****	**0.590*****
VSMI	**0.333*****	**0.536*****	**0.338*****	**0.547*****
VSTOXX	**0.300*****	**0.506*****	**0.309*****	**0.523*****
VHSI	**0.706*****	**0.868*****	**0.702*****	**0.866*****
JNIV	**0.588*****	**0.802*****	**0.605*****	**0.812*****
KSVKOSPI	**0.636*****	**0.820*****	**0.651*****	**0.831*****
NIFVIX	**0.889*****	**0.977*****	**0.890*****	**0.976*****
AVIX	**0.639*****	**0.822*****	**0.640*****	**0.820*****
GVZ	**0.934*****	**0.988*****	**0.936*****	**0.988*****
OVX	**0.946*****	0.992	**0.943*****	0.992

Notes. Relative MSE and QLIKE losses as defined in Section 3.1 with arguments in the column headers. *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Giacomini and White (2006). Entries in bold indicate cases where the numerator model, which includes GIV, performs significantly better than the denominator model that excludes GIV.

Table 3: Realized variance data

Market	RV	Stock index
United States	SP	S&P 500 Index
United States	DJI	Dow-Jones Industrial Average
United States	Nasdaq	Nasdaq 100
United States	Russell	Russell 2000
United Kingdom	FTSE	FTSE 100
Italy	FTMIB	FTSE MIB
Germany	GDAXI	DAX 30
France	CAC40	CAC 40
Spain	IBEX	IBEX 35
Japan	N225	Nikkei 225
Norway	OSEAX	Oslo Exchange All-share Index
Finland	OMXHPI	OMX Helsinki All Share Index
Sweden	OMXSPI	OMX Stockholm All Share Index
The Netherlands	AEX	AEX index
Euro area	STOXX50	EURO STOXX 50
Switzerland	SSMI	Swiss Stock Market Index
Hong Kong	HSI	Hang Seng Index
South Korea	KS11	KOSPI
Belgium	BFX	Bell 20
Australia	AORD	All Ordinaries
Brazil	BVSP	BVSP BOVESPA
India	NSEI	Nifty 50
Pakistan	KSE	Karachi SE 100
Mexico	MXX	IPC Mexico
China	SSEC	Shanghai Composite Index
India	BSESN	S&P BSE Sensex
Canada	GSPTSE	S&P/TSX Composite index

Table 4: Oos RV forecasts: relative losses

	Rel-MSE(·)			*Rel*-QLIKE(·)		
	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$
SP	**0.622*****	1.100***	1.166***	**0.606*****	1.109***	1.175***
DJI	**0.594*****	1.073***	1.121***	**0.569*****	1.077**	1.129***
Nasdaq	**0.721*****	1.087***	1.106***	**0.709*****	1.089***	1.105***
Russell	**0.714*****	1.057***	1.063***	**0.700*****	1.057**	1.059**
FTSE	**0.662*****	**0.905*****	**0.958****	**0.644*****	**0.899*****	0.955
FTMIB	**0.747*****	**0.923*****	**0.947*****	**0.731*****	**0.915*****	**0.938*****
GDAXI	**0.676*****	**0.890*****	**0.922*****	**0.657*****	**0.874*****	**0.902*****
CAC40	**0.654*****	**0.886*****	**0.924*****	**0.633*****	**0.872*****	**0.903*****
IBEX	**0.765*****	**0.920*****	**0.962***	**0.752*****	**0.912*****	0.952
N225	**0.830*****	**0.941*****	**0.962****	**0.823*****	**0.944*****	**0.966****
OSEAX	**0.717*****	**0.931*****	0.972	**0.710*****	**0.931*****	0.972
OMXHPI	**0.737*****	**0.935*****	0.977	**0.722*****	**0.927*****	0.969
OMXSPI	**0.661*****	**0.902*****	**0.921*****	**0.640*****	**0.891*****	**0.909*****
AEX	**0.610*****	**0.888*****	**0.900*****	**0.596*****	**0.878*****	**0.883*****
STOXX50	**0.648*****	**0.874*****	**0.907*****	**0.630*****	**0.863*****	**0.890*****
SSMI	**0.617*****	**0.877*****	**0.893*****	**0.613*****	**0.871*****	**0.885*****
OMXC20	**0.833*****	**0.963*****	0.986	**0.822*****	**0.959*****	0.983
HSI	**0.887****	0.983	0.993	**0.889****	0.982	0.992
KS11	**0.891*****	**0.992***	0.991	**0.887*****	0.993	0.991
BFX	**0.680*****	**0.900*****	**0.918*****	**0.668*****	**0.892*****	**0.910*****
AORD	**0.764*****	**0.947****	**0.971***	**0.759*****	**0.943****	**0.966***
BVSP	**0.895*****	0.989	0.994	**0.877*****	0.983	0.987
NSEI	**0.858*****	**0.956*****	**0.975****	**0.862*****	**0.957*****	**0.974****
KSE	**0.959****	**0.991***	**0.986****	**0.953****	**0.992****	**0.987****
MXX	**0.870****	0.995	0.999	**0.867****	0.995	1.001
SSEC	**0.959****	**0.988****	0.992	**0.956*****	**0.988****	0.991
BSESN	**0.860*****	**0.957*****	**0.973****	**0.866*****	**0.958*****	**0.973***
GSPTSE	**0.670*****	1.001	1.013	**0.666*****	0.993	1.003

Notes: Relative MSE and QLIKE losses as defined in Section 3.1 with arguments in the column headers. *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Giacomini and White (2006). Entries in bold indicate cases where the numerator model, which includes GIV, performs significantly better than the denominator model that excludes GIV.

Table 5: *GVRP* AND EXPECTED EQUITY RETURNS (HAR-RV)

	Horizons				
	1	6	12	18	24
SP	−0.196	0.314***	0.369***	0.363***	0.258***
DJI	−0.214	0.257***	0.315**	0.320***	0.219***
Nasdaq	−0.112	0.297***	0.215*	0.133	0.036
Russell	−0.152	0.286**	0.384***	0.358***	0.291***
FTSE	−0.239	0.133	0.313***	0.424***	0.377***
FTMIB	−0.209	0.017	0.103	0.106	0.046
GDAXI	−0.225	0.203***	0.276***	0.296***	0.243**
CAC40	−0.260	0.093	0.226*	0.270**	0.182**
IBEX	−0.191	−0.053	0.095	0.112	0.091
N225	−0.181	0.063	0.032	0.139**	0.137
OSEAX	−0.172	0.202**	0.270**	0.288**	0.271**
OMXHPI	−0.204	0.162*	0.107	0.123	0.006
OMXSPI	−0.192	0.239**	0.253*	0.256**	0.063
AEX	−0.170	0.147	0.280**	0.300**	0.131
TOXX50	−0.223	0.109	0.224**	0.241**	0.150*
SSMI	−0.200	0.095	0.189**	0.350***	0.282**
OMXC20	−0.136	0.226***	0.195**	0.223**	0.139*
HSI	−0.149	0.100	0.116	0.027	0.022
KS11	−0.032	0.379**	0.383**	0.296**	0.174
BFX	−0.270	0.063	0.187*	0.211**	0.140*
AORD	−0.259	0.148	0.230**	0.348***	0.215**
BVSP	−0.171	0.122*	0.039	−0.082	−0.177
NSEI	−0.190	0.156	0.261*	0.229	0.085
KSE	−0.170	0.185**	0.260***	0.266**	0.276**
MXX	−0.110	0.311**	0.506***	0.532***	0.398***
SSEC	−0.079	0.028	−0.028	−0.041	−0.165
BSESN	−0.198	0.133	0.238*	0.205	0.070
GSPTSE	−0.231	0.188*	0.301**	0.314**	0.196

Notes: Estimated slope coefficients in the return predictive regression (12) with $\hat{c}_h^i = 0$. VRP is based on expected realized volatility estimated by a HAR model. *, ** and *** denote 10-, 5- and 1-percent statistical significance using Newey and West (1987) standard errors.

Table 6: *GVRP* AND EXPECTED EQUITY RETURNS WITH CONTROLS (HAR-RV)

	Horizons				
	1	6	12	18	24
			Panel A: control = US VRP		
SP	−0.224	0.214	0.374*	0.453**	0.364**
DJI	−0.254	0.197	0.419**	0.492***	0.477***
Nasdaq	0.003	0.346*	0.192	0.194	0.033
Russell	−0.356	0.174	0.510**	0.470***	0.428***
FTSE	−0.462	−0.080	0.388**	0.562***	0.662***
FTMIB	−0.578	−0.314	−0.045	0.080	0.249*
GDAXI	−0.335	0.132	0.391**	0.471***	0.380**
CAC40	−0.577	−0.212	0.144	0.318**	0.443***
IBEX	−0.582	−0.421	−0.009	0.115	0.322**
N225	−0.442	−0.062	0.041	0.256*	0.279
OSEAX	−0.393	−0.037	0.292*	0.317*	0.558***
OMXHPI	−0.368	0.066	0.122	0.275*	0.246*
OMXSPI	−0.339	0.127	0.255	0.334*	0.110
AEX	−0.341	−0.040	0.272	0.402*	0.363**
STOXX50	−0.467	−0.122	0.193	0.324**	0.350**
SSMI	−0.278	−0.099	0.152	0.430**	0.364**
OMXC20	−0.163	0.185	0.109	0.123	0.037
HSI	−0.407	0.068	0.361***	0.306*	0.369
KS11	−0.133	0.315	0.508*	0.343	0.302
BFX	−0.467	−0.122	0.227	0.328**	0.359**
AORD	−0.507	−0.031	0.328*	0.496***	0.596***
BVSP	−0.216	0.219*	0.430***	0.166	0.271*
NSEI	−0.390	0.040	0.286	0.330	0.294*
KSE	−0.165	0.271**	0.506***	0.445**	0.297**
MXX	−0.294	0.153	0.591***	0.526***	0.452**
SSEC	−0.311	−0.070	−0.142	−0.065	−0.238
BSESN	−0.411	0.004	0.242	0.289	0.268
GSPTSE	−0.483	−0.088	0.237	0.323	0.417*
			Panel B: control = local VRP		
SP	−0.224	0.214	0.374*	0.453**	0.364**
DJI	−0.159	0.286*	0.340*	0.449***	0.503***
Nasdaq	0.053	0.403**	0.281	0.259	−0.112
FTSE	−0.109	0.092	0.416***	0.539***	0.527***
FTMIB	−0.082	−0.133	−0.249	−0.332	−0.344
GDAXI	−0.216	0.236	0.270	0.478**	0.557***
SSMI	−0.005	0.216*	0.283***	0.435***	0.373**
STOXX50	−0.206	0.123	0.410***	0.405***	0.212**
HSI	0.331**	0.365***	0.018	−0.178	−0.121
N225	0.039	0.056	−0.048	0.066	0.057
AORD	−0.229	0.199*	0.387***	0.492***	0.309***

Notes: Estimated slope coefficients in the return predictive regression (12) with X_t equal to the US VRP (Panel A) or the local VRP (Panel B). VRP is based on expected realized volatility estimated by a HAR model. *, ** and *** denote 10-, 5- and 1-percent statistical significance using Newey and West (1987) standard errors.

Table 7: *GVRP* AND EXPECTED EQUITY RETURNS (RW-RV)

	Horizons				
	1	6	12	18	24
SP	−0.019	0.334***	0.348***	0.309***	0.201**
DJI	−0.054	0.280***	0.287***	0.272***	0.167**
Nasdaq	0.002	0.255***	0.179**	0.101	0.037
Russell	0.066	0.320***	0.329***	0.299***	0.237**
FTSE	−0.028	0.218*	0.328***	0.386***	0.290***
FTMIB	0.004	0.127	0.143	0.123	0.041
GDAXI	−0.040	0.226***	0.245***	0.251***	0.231**
CAC40	−0.041	0.194*	0.246**	0.253**	0.131*
IBEX	−0.010	0.081	0.152*	0.127	0.082
N225	−0.029	0.082	0.022	0.102	0.100
OSEAX	0.037	0.270***	0.282***	0.270***	0.194***
OMXHPI	−0.046	0.172**	0.113	0.075	−0.013
OMXSPI	−0.024	0.236**	0.236**	0.197**	0.046
AEX	−0.003	0.203*	0.269**	0.253***	0.084
TOXX50	−0.028	0.182*	0.230**	0.216**	0.126
SSMI	−0.104	0.134*	0.178**	0.278***	0.216*
OMXC20	−0.019	0.200**	0.182*	0.181**	0.130*
HSI	0.037	0.111	0.087	0.005	0.042
KS11	0.119	0.373***	0.317***	0.231***	0.137*
BFX	−0.127	0.138	0.182*	0.174**	0.091
AORD	−0.062	0.216**	0.236**	0.279***	0.123
BVSP	−0.039	0.113	0.009	−0.081	−0.190
NSEI	−0.026	0.210**	0.280**	0.205*	0.055
KSE	−0.079	0.169**	0.191**	0.205**	0.229*
MXX	0.049	0.353**	0.467***	0.455***	0.302***
SSEC	0.036	0.017	−0.006	−0.040	−0.129
BSESN	−0.031	0.193*	0.262**	0.187*	0.043
GSPTSE	−0.026	0.261**	0.334***	0.297**	0.124

Notes: Estimated slope coefficients in the return predictive regression (12) with $\hat{c}_h^i = 0$. VRP is based on expected realized volatility obtained by assuming a random walk. *, ** and *** denote 10-, 5- and 1-percent statistical significance using Newey and West (1987) standard errors.

Table 8: *GVRP* AND EXPECTED EQUITY RETURNS WITH CONTROLS (RW-RV)

	Horizons				
	1	6	12	18	24
			Panel A: control = US VRP		
SP	0.001	0.041***	0.047***	0.048***	0.049***
DJI	−0.002	0.036***	0.042***	0.043***	0.043***
Nasdaq	0.032	0.071***	0.072***	0.074***	0.074***
Russell	−0.037	0.025*	0.042***	0.041***	0.041***
FTSE	−0.035	0.001	0.009	0.009	0.009*
FTMIB	−0.080	−0.023	−0.005	0.000	0.005
GDAXI	−0.027	0.022*	0.031***	0.032***	0.032***
CAC40	−0.049	0.001	0.015*	0.018**	0.020***
IBEX	−0.082	−0.036	−0.017	−0.012	−0.010
N225	−0.032	0.024	0.037**	0.043***	0.045***
OSEAX	−0.012	0.029**	0.039***	0.038***	0.041***
OMXHPI	−0.037	0.009	0.015	0.021**	0.022***
OMXSPI	−0.019	0.026**	0.034***	0.037***	0.036***
AEX	−0.022	0.014	0.025**	0.028***	0.028***
STOXX50	−0.053	−0.004	0.008	0.011	0.012**
SSMI	−0.013	0.011	0.019**	0.022***	0.023***
OMXC20	0.017	0.047***	0.049***	0.051***	0.053***
HSI	−0.050	−0.006	0.007	0.007	0.008
KS11	−0.028	0.006	0.016	0.015	0.015**
BFX	−0.037	0.001	0.014	0.015*	0.017**
AORD	−0.042	0.005	0.016**	0.018***	0.019***
BVSP	−0.030	0.017	0.029**	0.025**	0.028**
NSEI	−0.011	0.030**	0.039***	0.042***	0.043***
KSE	0.013	0.044**	0.056***	0.053***	0.051***
MXX	−0.024	0.007	0.014*	0.013*	0.012**
SSEC	−0.058	−0.003	0.001	0.007	0.007
BSESN	−0.011	0.030**	0.039***	0.041***	0.043***
GSPTSE	−0.029	0.007	0.014*	0.014**	0.016***
			Panel B: control = local VRP		
SP	0.001	0.041***	0.047***	0.048***	0.049***
DJI	0.004	0.035***	0.038***	0.039***	0.039***
Nasdaq	0.053**	0.086***	0.091***	0.098***	0.093***
FTSE	0.001	0.009	0.012**	0.011**	0.009**
FTMIB	0.025	−0.017	−0.043	−0.039	−0.029
GDAXI	−0.020	0.015	0.017*	0.028***	0.033***
SSMI	0.017	0.021***	0.021***	0.022***	0.022***
STOXX50	−0.023	0.008	0.019*	0.018**	0.014**
HSI	0.075***	0.003	−0.012	−0.004	0.002
N225	0.095***	0.020	0.019	0.022**	0.031***
AORD	0.002	0.019**	0.023***	0.022***	0.018***

Notes: Estimated slope coefficients in the return predictive regression (12) with X_t equal to the US VRP (Panel A) or the local VRP (Panel B). VRP is based on expected realized volatility obtained assuming a random walk. *, ** and *** denote 10-, 5- and 1-percent statistical significance using Newey and West (1987) standard errors.

Table 9: *GVRP* AND EXPECTED EQUITY RETURNS USING PANEL REGERSSIONS

	Horizons				
	1	6	12	18	24
			Panel A: no control		
HAR	−0.177	0.150***	0.198***	0.197***	0.114***
RW	−0.123	0.168***	0.217***	0.198***	0.115***
			Panel B: control = US VRP		
HAR	−0.347	0.025	0.234***	0.275***	0.253***
RW	−0.311	0.085***	0.195***	0.182***	0.112***
			Panel C: control = local VRP		
HAR	−0.108	0.148***	0.186***	0.213***	0.142**
RW	−0.190	0.117***	0.179***	0.189***	0.129***

Notes: Estimated slope coefficients in the panel regression (13) with $\hat{c}_h = 0$ X_t equal to the US VRP (Panel B) or the local VRP (Panel C). In the rows denoted by HAR the VRP is based on expected realized volatility estimated by a HAR model; in the rows denoted by RW the expected realized volatility is obtained assuming a random walk. *, ** and *** denote 10-, 5- and 1-percent statistical significance using Newey and West (1987) standard errors.

Table 10: Out of sample expected equity returns R^2_{OS} (HA)

	Horizons					
	1	2	3	4	5	6
Panel A: *GVRP*						
SP	**15.189****	**13.657****	**13.666*****	**12.270*****	**14.012*****	**14.605*****
DJI	**13.959****	**10.864*****	**11.355*****	**11.032*****	**12.098*****	**13.657*****
Nasdaq	**13.342****	**13.672****	**10.267****	**5.006***	**4.902***	−0.841
Russell	**11.713****	**12.481*****	**10.182*****	**11.150*****	**10.992*****	**10.553*****
FTSE	−2.670	−14.573*	−18.851	−14.861	−13.970	−12.461
FTMIB	1.296	−0.193**	−0.163**	**3.108****	**2.585****	**3.610****
GDAXI	**13.623***	**9.137****	**3.745****	**1.862***	**3.511****	**4.562****
CAC40	**3.892***	**0.564****	**2.148****	**6.411****	**6.811****	**8.728****
IBEX	−6.693	−17.456	−20.378	−18.229	−24.179	−26.094
N225	**15.241****	**11.163*****	**8.358*****	**10.585****	**9.729****	9.137**
OSEAX	**15.118****	**12.796*****	**12.241*****	**15.702*****	**16.942*****	**19.905*****
OMXHPI	**9.348***	**4.766****	**2.281****	−0.258*	**0.452***	−2.001
OMXSPI	**9.058***	**8.644****	**12.335*****	**9.000*****	**10.456*****	**10.141*****
AEX	**8.656***	**0.666****	**2.211****	**8.734****	**11.758****	**13.027****
STOXX50	**3.340***	−2.548*	−5.298*	−4.840	−5.237	−5.466
SSMI	−5.054*	−21.864*	−15.066**	−9.362*	−6.223*	−8.289**
OMXC20	**18.288****	**12.100****	**12.578*****	**11.525*****	**13.549*****	**12.040*****
HSI	−17.394	−18.448	−23.653	−22.405	−26.944	−29.685
KS11	**11.950***	**11.746****	**7.109****	**3.571***	**1.963**	0.021
BFX	**3.367***	−6.152*	−8.009	−5.173	−6.521	−6.932
AORD	**5.996***	**5.722****	**2.733*****	**3.703****	**2.369****	**1.169****
BVSP	**7.987***	**12.907****	**7.950*****	**9.471*****	10.180***	9.783***
NSEI	**11.003****	**19.217*****	**16.429*****	**16.446*****	**15.416*****	**16.174*****
KSE	**11.252*****	**19.433*****	**18.337*****	**17.550*****	**21.061*****	25.095***
MXX	−0.584	−3.592**	**0.060****	**1.219***	0.160	0.213
SSEC	−5.338	1.156*	−8.936	−14.893	−19.879	−21.487
BSESN	**9.998****	**18.164*****	**16.194*****	**17.029*****	**16.029*****	**16.539*****
GSPTSE	**9.244***	**8.489****	**4.209*****	**5.028****	**4.443****	**8.141****
Panel B: US VRP						
SP	11.289	8.866**	6.806***	8.112**	6.924***	8.597***
DJI	9.473	5.844**	5.916***	7.452**	6.997***	10.116***
Nasdaq	10.262*	9.987**	5.567**	3.005	0.357	−4.336
Russell	8.087	6.573**	4.061***	7.448**	7.438**	9.048***
FTSE	−4.309	−12.599	−18.787	−19.356	−16.835	−14.976
FTMIB	−0.918	−0.974**	−3.230	−0.682*	−1.484*	1.099*
GDAXI	9.576	5.772**	0.090	−0.830	0.236	3.384*
CAC40	−0.333	−1.227**	−1.958	1.440*	1.302	4.479*
IBEX	−9.329	−18.171	−23.984	−22.211	−26.704	−27.093
N225	9.420	5.400**	3.518**	7.459*	7.672**	**9.834*****
OSEAX	9.226*	6.506***	6.614***	9.133***	10.706***	14.502***
OMXHPI	7.904	0.273*	−5.991	−4.609	−5.032	−4.445
OMXSPI	5.812	6.146**	4.871**	5.383**	4.428**	7.110**
AEX	4.330	−0.584**	−1.551	1.329*	3.824*	7.784*
STOXX50	−0.909	−3.722*	−8.889	−8.927	−9.873	−8.135
SSMI	−3.970	−12.667*	−12.038	−12.437	−11.932	−10.526
OMXC20	13.685	8.949**	4.983**	4.941**	6.347***	7.061***
HSI	−16.630	−18.327	−21.914	−22.996	−24.455	−25.670
KS11	6.198	3.575	−2.457	−0.803	−0.740	0.374
BFX	0.439	−7.013	−11.357	−9.630	−10.828	−9.034
AORD	6.673	4.384**	−2.499*	0.255*	−1.430*	−0.395*
BVSP	7.272*	8.938**	6.338***	9.305***	**10.769*****	**11.853*****
NSEI	6.347*	10.699**	8.313***	10.205**	9.229***	11.096***
KSE	10.928***	14.196***	13.468***	16.097***	20.399***	**25.157*****
MXX	−4.574	−6.740	−6.973	−4.955	−5.170	−2.629
SSEC	−5.071	1.660	−11.152	−14.351	−18.669	−18.987
BSESN	5.626*	10.291**	8.745***	10.923**	9.786***	11.508***
GSPTSE	7.277	5.286**	−1.614*	−0.886*	−1.875*	2.521**
Panel C: Cross-market averages						
GVRP	6.612	4.376	2.644	3.228	3.088	2.994
US VRP	3.707	1.476	−1.968	−0.721	−1.022	0.689
ΔR^2_{OS}	2.905	2.900	4.612	3.949	4.110	2.305

Notes: R^2_{OS} (HA) obtained using panel regressions and RW realized volatility. In Panel A and B, *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Clark and West (2006). Entries in bold indicate that the R^2_{OS} (HA) in Panel A (Panel B) is positive, significant and larger than the corresponding R^2_{OS} (HA) reported in Panel B (Panel A).

Table 11: CURRENCY PORTFOLIOS WITH VARIANCE RISK PREMIUM GAPS

	$GVRP$	$USVRP$	$GVRP^a$
Mean	1.88**	0.03	1.42*
Irdiff	−0.78	−0.17	−0.28
Sharpe Ratio	0.62	0.01	0.44
Std	10.54	10.89	11.21
Skewness	0.43	0.84	0.62
Kurtosis	5.35	5.40	5.06
MDD	4.08	7.98	4.19
TO	31.37	66.13	54.15

Notes: Irdiff, is the forward premium defined as in equation (18). MDD and TO stand for maximum drawdown and turnover, respectively. Mean, Irdiff and MDD are reported in percentage terms.

Figures

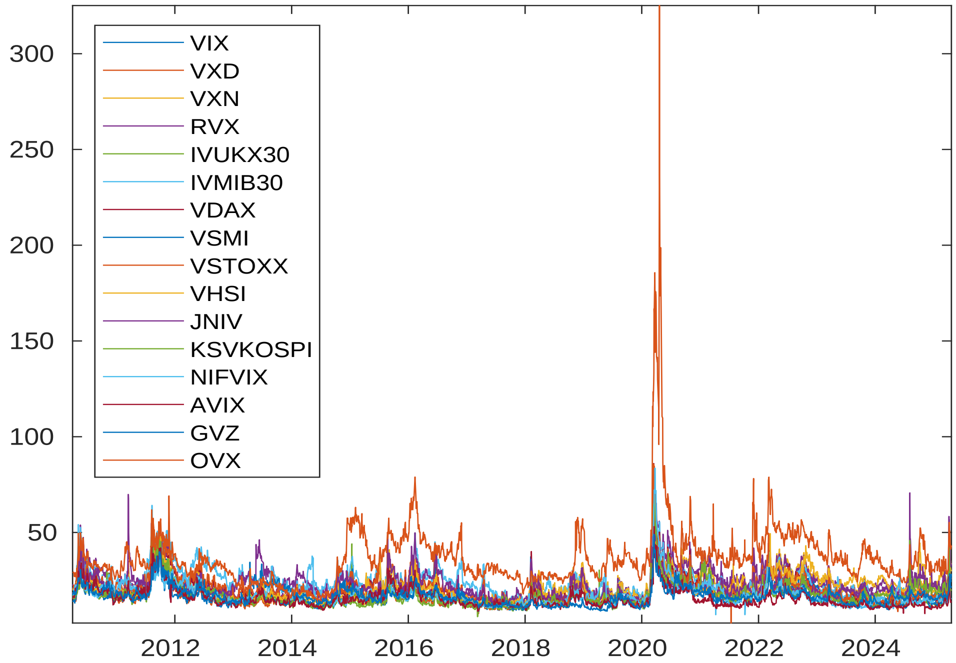


Figure 1: International implied volatilities

Notes: The names in the legend are defined in Table 1.

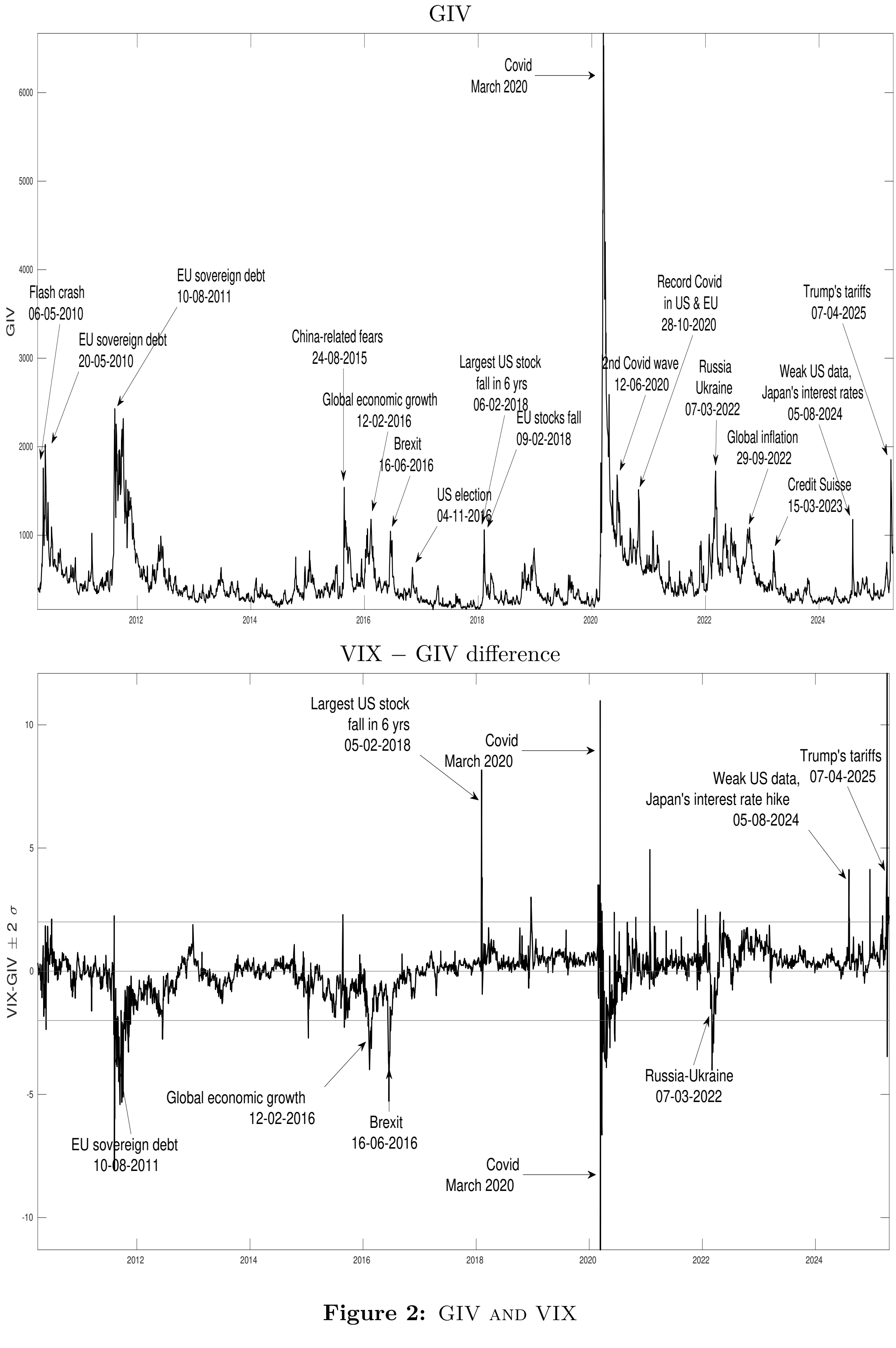
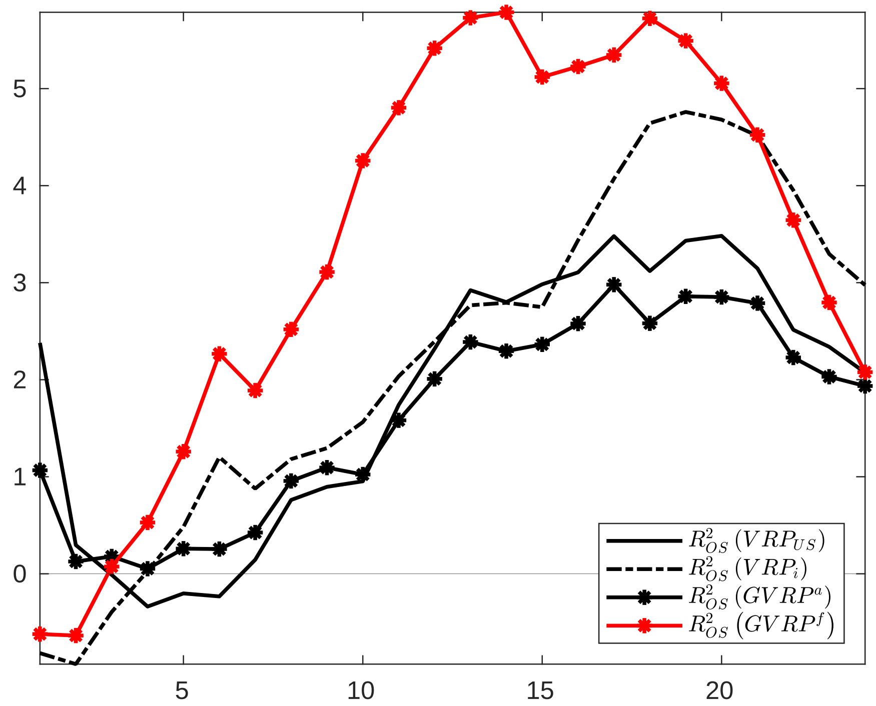


Figure 2: GIV AND VIX

Individual Country Regressions



Panel Regressions

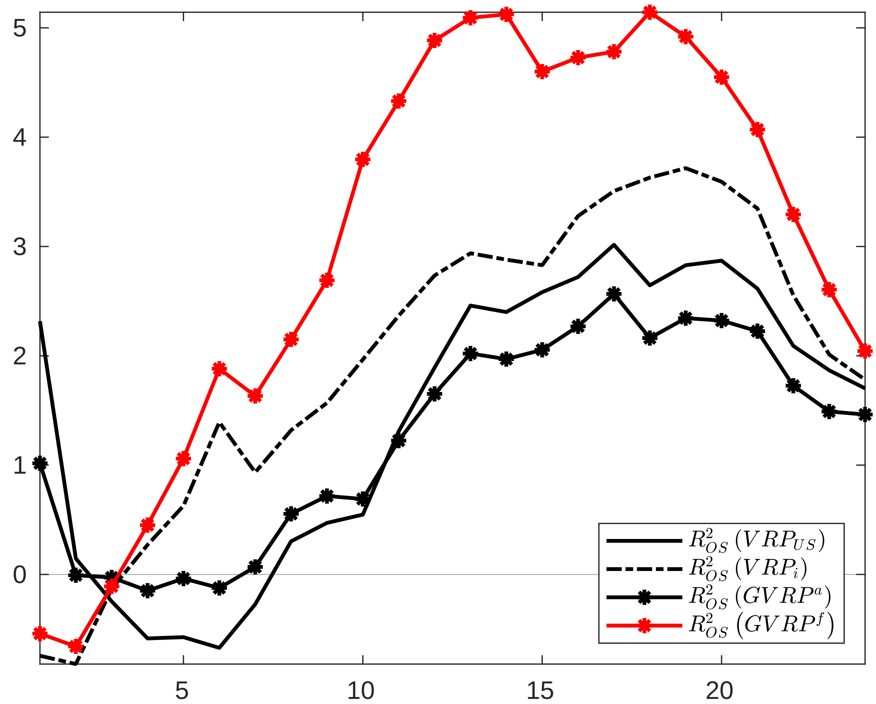
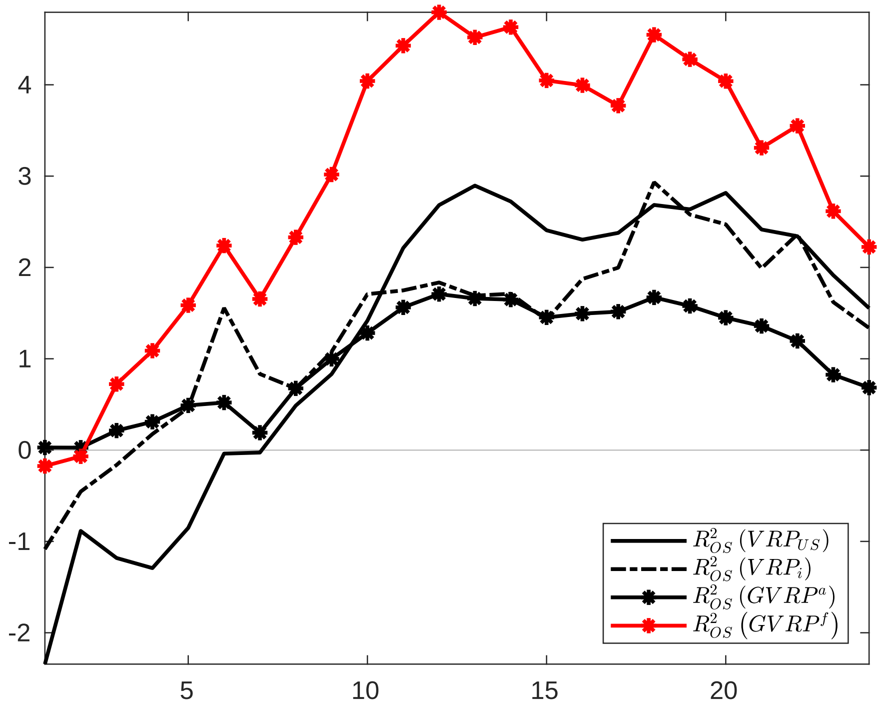


Figure 3: VRP AND EXPECTED EQUITY RETURNS (HAR-RV)

Notes: Expected realized volatility is obtained using a HAR model. All lines in the figure report relative mean square gains with respect to a benchmark b measured by $R^2_{OS}\,(b)$ as in equation (17). $R^2_{OS}\,(b)$ are reported in percentage terms and averaged across markets. The abscissa corresponds to the predictive horizons $h = 1, 2, \ldots, 24$.

Individual Country Regressions



Panel Regressions

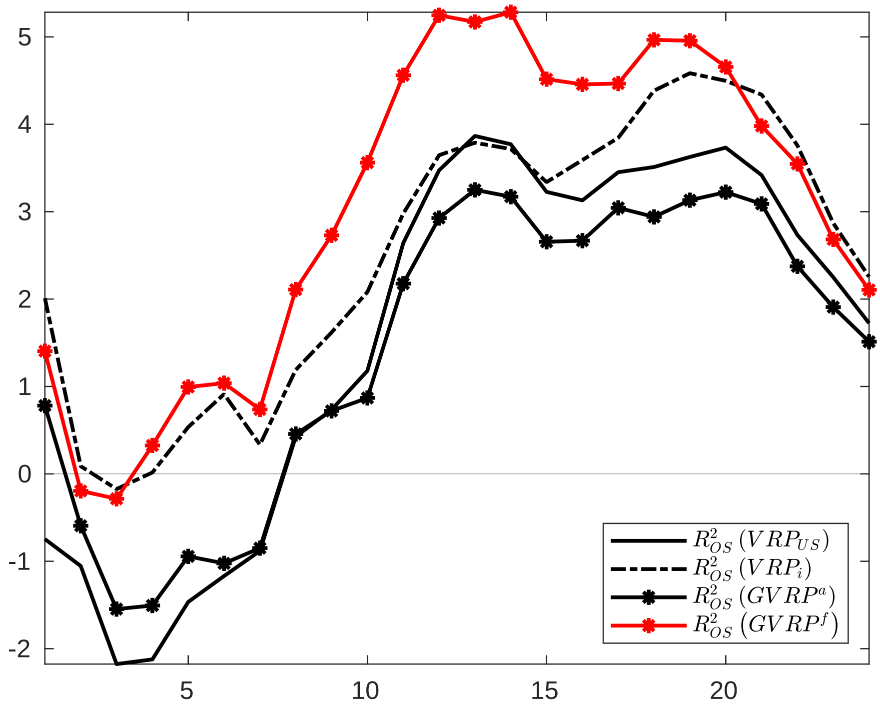


Figure 4: VRP AND EXPECTED EQUITY RETURNS (RW-RV)

Notes: Expected realized volatility is obtained assuming a randowm walk. All lines in the figure report relative mean square gains with respect to a benchmark b measured by $R^2_{OS}\,(b)$ as in equation (17). $R^2_{OS}\,(b)$ are reported in percentage terms and averaged across markets. The abscissa corresponds to the predictive horizons $h = 1, 2, \ldots, 24$.

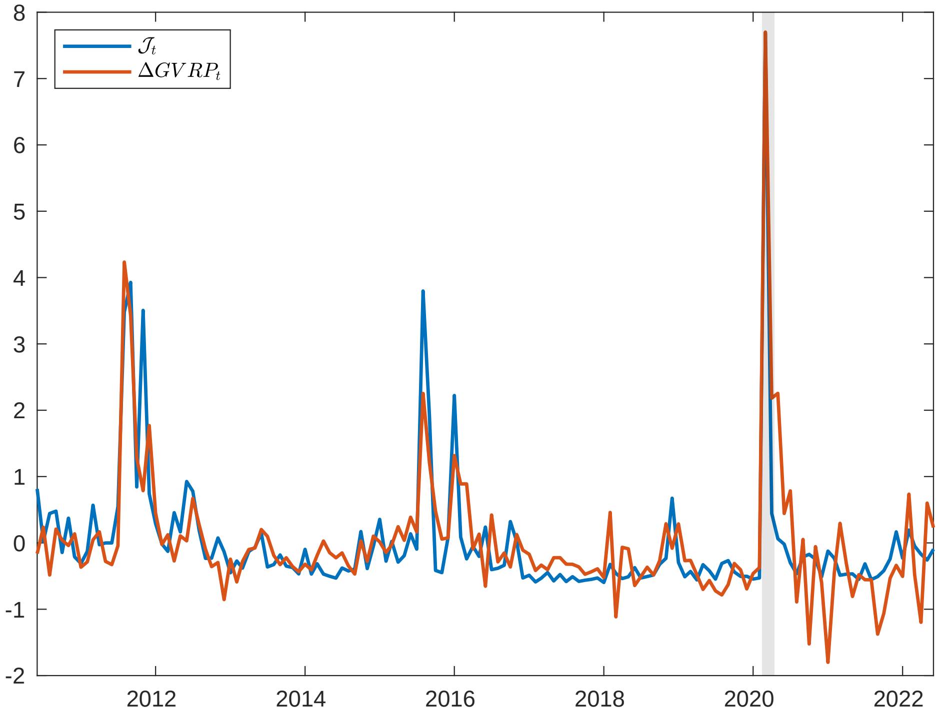


Figure 5: $\Delta GVRP_t \equiv GVRP_t - GVRP^a_t$ AND GLOBAL JUMPS $\mathcal{J}_t$

Notes: $\Delta GVRP_t$ and $\mathcal{J}_t$ are both standardized.

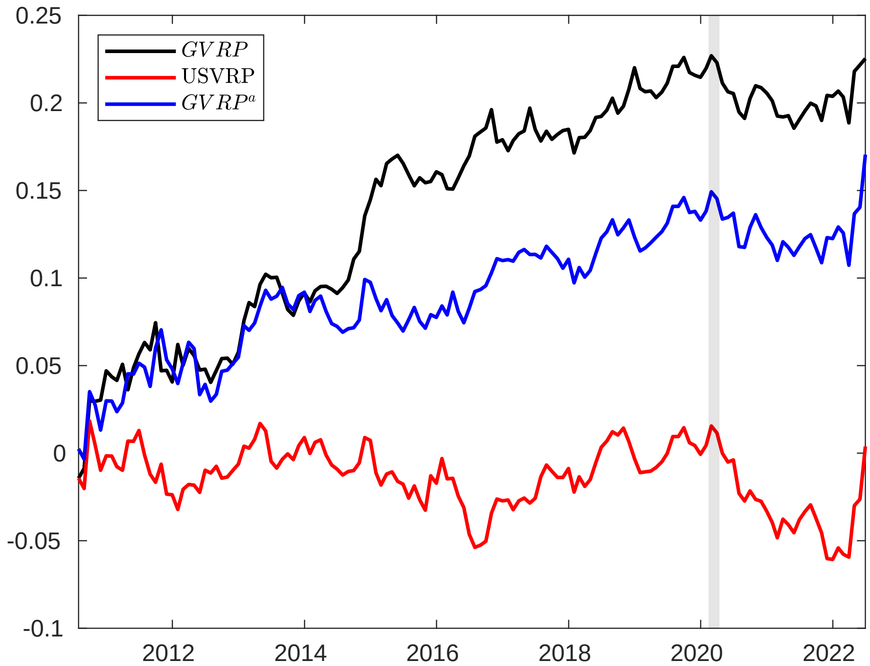


Figure 6: CUMULATIVE RETURNS OF CURRENCY PORTFOLIOS

Notes: Cumulative returns of the portfolios with the strategy described in Section 5 based on variance risk premia gaps between a reference global VRP and local VRP. $GVRP$, $GVRP^a$ and the US VRP are used as reference global VRP as in the legend. The shaded area denotes the dates of the covid pandemics recession in the US determined by the NBER's Business Cycle Dating Committee.

Appendix

Table A.1: IV and LOG(IV): summary statistics

	IV levels				*logIV*			
	Mean	Std.Dev.	Skewness	Kurtosis	Mean	Std.Dev.	Skewness	Kurtosis
VIX	18.382	7.087	2.483	14.731	2.854	0.323	0.809	3.880
VXD	17.270	6.434	2.586	14.353	2.797	0.307	0.916	4.680
VXN	21.290	7.172	1.751	8.941	3.011	0.299	0.644	3.151
RVX	23.551	7.956	1.907	9.249	3.112	0.295	0.744	3.507
IVUKX30	17.109	6.354	2.410	13.138	2.787	0.310	0.908	4.079
IVMIB30	24.700	7.801	1.794	9.220	3.164	0.285	0.474	3.804
VDAX	20.676	7.179	2.401	14.040	2.982	0.294	0.848	4.068
VSMI	16.331	5.521	3.539	26.323	2.753	0.267	1.252	5.986
VSTOXX	21.328	7.493	2.113	11.929	3.100	0.306	0.640	3.626
VHSI	21.329	6.042	1.477	7.314	3.025	0.261	0.437	3.324
JNIV	22.309	6.234	2.091	11.389	3.073	0.246	0.755	4.301
KSVKOSPI	17.617	5.957	2.585	14.539	2.826	0.281	0.991	4.671
NIFVIX	17.889	6.091	3.437	26.239	2.842	0.276	1.001	5.363
AVIX	15.515	4.963	2.205	10.489	2.702	0.270	1.062	4.246
GVZ	17.058	4.585	1.297	6.675	2.804	0.254	0.256	3.312
OVX	36.938	17.061	5.804	62.914	3.546	0.335	0.811	6.740

Table A.2: Oos IV forecasts in levels

	Rel-MSE(·)		*Rel*-QLIKE(·)	
	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$
VIX	**0.772*****		**0.756*****	
VXD	**0.804*****	1.363***	**0.754*****	1.220***
VXN	**0.806*****	1.076*	**0.824*****	1.038**
RVX	**0.793*****	**0.835*****	**0.798*****	**0.832*****
IVUKX30	**0.311*****	**0.532*****	**0.304*****	**0.532*****
IVMIB30	**0.582*****	**0.817*****	**0.646*****	**0.856*****
VDAX	**0.353*****	**0.597*****	**0.361*****	**0.604*****
VSMI	**0.354*****	**0.529*****	**0.337*****	**0.538*****
VSTOXX	**0.291*****	**0.518*****	**0.307*****	**0.554*****
VHSI	**0.677*****	**0.839*****	**0.686*****	**0.841*****
JNIV	**0.589*****	**0.828*****	**0.601*****	**0.817*****
KSVKOSPI	**0.568*****	**0.784*****	**0.633*****	**0.818*****
NIFVIX	**0.864*****	0.968	**0.868*****	**0.958*****
AVIX	0.709	**0.813*****	**0.687*****	**0.810*****
GVZ	**0.895*****	0.992	**0.907*****	0.993
OVX	0.999	0.998	0.965	0.985

Notes: Relative MSE and QLIKE losses as defined in Section 3.1 with arguments in the column headers. *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Giacomini and White (2006). Entries in bold indicate cases where the numerator model, which includes GIV, performs significantly better than the denominator model that excludes GIV.

Table A.3: Oos RV forecasts: relative losses (cross-sectional average GRV)

	Rel-MSE(·)			*Rel*-QLIKE(·)		
	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$
SP	**0.622*****	1.100***	1.162***	**0.606*****	1.109***	1.172***
DJI	**0.594*****	1.073***	1.114***	**0.569*****	1.077**	1.124***
Nasdaq	**0.721*****	1.087***	1.105***	**0.709*****	1.089***	1.105***
Russell	**0.714*****	1.057***	1.061***	**0.700*****	1.057**	1.060**
FTSE	**0.662*****	**0.905*****	**0.958****	**0.644*****	**0.899*****	0.957
FTMIB	**0.747*****	**0.923*****	**0.947*****	**0.731*****	**0.915*****	**0.936*****
GDAXI	**0.676*****	**0.890*****	**0.915*****	**0.657*****	**0.874*****	**0.896*****
CAC40	**0.654*****	**0.886*****	**0.920*****	**0.633*****	**0.872*****	**0.900*****
IBEX	**0.765*****	**0.920*****	**0.956****	**0.752*****	**0.912*****	**0.945****
N225	**0.830*****	**0.941*****	**0.969****	**0.823*****	**0.944*****	**0.972***
OSEAX	**0.717*****	**0.931*****	0.974	**0.710*****	**0.931*****	0.975
OMXHPI	**0.737*****	**0.935*****	**0.969***	**0.722*****	**0.927*****	**0.961****
OMXSPI	**0.661*****	**0.902*****	**0.921*****	**0.640*****	**0.891*****	**0.909*****
AEX	**0.610*****	**0.888*****	**0.904*****	**0.596*****	**0.878*****	**0.889*****
STOXX50	**0.648*****	**0.874*****	**0.910*****	**0.630*****	**0.863*****	**0.894*****
SSMI	**0.617*****	**0.877*****	**0.885*****	**0.613*****	**0.871*****	**0.874*****
OMXC20	**0.833*****	**0.963*****	0.986	**0.822*****	**0.959*****	0.983
HSI	**0.887****	0.983	0.999	**0.889****	0.982	0.998
KS11	**0.891*****	0.992*	0.995	**0.887*****	0.993	0.996
BFX	**0.680*****	**0.900*****	**0.924*****	**0.668*****	**0.892*****	**0.916*****
AORD	**0.764*****	**0.947****	**0.978***	**0.759*****	**0.943****	**0.971***
BVSP	**0.895*****	0.989	0.993	**0.877*****	0.983	0.987
NSEI	**0.858*****	**0.956*****	**0.982***	**0.862*****	**0.957*****	0.983
KSE	**0.959****	0.991*	0.992	**0.953****	**0.992****	**0.993****
MXX	**0.870****	0.995	0.997	**0.867****	0.995	1.000
SSEC	**0.959****	**0.988****	0.990	**0.956*****	**0.988****	0.990*
BSESN	**0.860*****	**0.957*****	**0.979***	**0.866*****	**0.958*****	0.979
GSPTSE	**0.670*****	1.001	1.008	**0.666*****	0.993	0.997

Notes: Relative MSE and QLIKE losses as defined in Section 3.1 with arguments in the column headers. *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Giacomini and White (2006). Entries in bold indicate cases where the numerator model, which includes GIV, performs significantly better than the denominator model that excludes GIV. As compared with Table 4, GRV is estimated using cross-sectional average of international realized volatilities. The 1st, 2nd, 4th and 5th columns are left for readability.

Table A.4: Oos RV forecasts in levels

	Rel-MSE(·)			*Rel*-QLIKE(·)		
	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$	$\frac{GIV}{bnc}$	$\frac{GIV}{VIX}$	$\frac{\text{GIV\&GRV}}{\text{VIX\&GRV}}$
SP	**0.501****	1.003	1.096	**0.582*****	0.939	0.989
DJI	**0.474****	0.914	0.955	**0.624*****	**0.857***	0.818
Nasdaq	**0.644*****	1.077**	1.096**	**0.690*****	1.071**	1.096***
Russell	**0.648*****	1.05	1.045	**0.711*****	1.045*	1.046**
FTSE	**0.603****	0.893	0.922	**0.631*****	**0.905*****	**0.928*****
FTMIB	**0.703***	**0.902***	0.906	**0.745*****	**0.891*****	**0.888*****
GDAXI	**0.553*****	**0.851*****	**0.840*****	**0.637*****	**0.881*****	**0.889*****
CAC40	**0.571*****	**0.841****	**0.815****	**0.639*****	**0.877*****	**0.854*****
IBEX	**0.729***	0.895	0.901	**0.787*****	**0.912*****	**0.913*****
N225	0.881	0.919	0.933	0.885	**0.884*****	**0.895*****
OSEAX	0.733	0.957	0.978	**0.745*****	**0.936*****	**0.960****
OMXHPI	**0.694*****	**0.923****	**0.919****	**0.753*****	**0.957***	**0.950****
OMXSPI	**0.589*****	**0.863****	**0.819*****	**0.647*****	**0.887*****	**0.856*****
AEX	**0.557*****	**0.826***	**0.725****	**0.577*****	**0.849*****	**0.791*****
STOXX50	**0.584****	**0.865****	**0.845***	**0.634*****	**0.872*****	**0.870*****
SSMI	**0.666***	0.936	0.924	**0.618*****	**0.860*****	**0.833*****
OMXC20	**0.797****	**0.954***	0.970	**0.827*****	**0.953*****	**0.960*****
HSI	0.956	0.946	0.949	0.919	**0.949****	**0.944****
KS11	0.841	0.971	0.961	0.925	0.981	0.972
BFX	**0.672*****	**0.916****	**0.881****	**0.698*****	**0.923*****	**0.883*****
AORD	**0.730*****	0.945	0.945	**0.713*****	**0.931*****	**0.939*****
BVSP	**0.787****	0.948	0.958	**0.896*****	0.989	0.993
NSEI	**0.839****	0.94	0.949	**0.852*****	**0.928*****	**0.954****
KSE	0.941	**0.995***	**0.994***	0.995	0.986	0.982
MXX	0.920	**0.979****	**0.995****	0.920	**0.961*****	**0.957*****
SSEC	0.991	**0.965****	**0.961****	1.065	**0.934*****	**0.920****
BSESN	**0.838****	0.943	0.944	**0.848*****	**0.925*****	**0.943*****
GSPTSE	**0.544***	1.015	1.034	**0.593*****	**0.888*****	**0.902****

Notes: Relative MSE and QLIKE losses as defined in Section 3.1 with arguments in the column headers. *, ** and *** denote 10-, 5- and 1-percent statistical significance using the test of Giacomini and White (2006). Entries in bold indicate cases where the numerator model, which includes GIV, performs significantly better than the denominator model that excludes GIV.

Table A.5: *GVRP* AND EXPECTED EQUITY RETURNS: IVX-WALD P-VALUES

	Horizons				
	1	6	12	18	24
			Panel A: control = US VRP		
SP	−0.224***	0.214	0.374	0.453*	0.364
DJI	−0.254***	0.197**	0.419**	0.492***	0.477
Nasdaq	0.003***	0.346	0.192*	0.194	0.033*
Russell	−0.356**	0.174***	0.510*	0.470***	0.428
FTSE	−0.462	−0.080**	0.388***	0.562***	0.662***
FTMIB	−0.578	−0.314	−0.045	0.080*	0.249
GDAXI	−0.335***	0.132**	0.391***	0.471***	0.380***
CAC40	−0.577	−0.212	0.144*	0.318***	0.443**
IBEX	−0.582	−0.421	−0.009**	0.115***	0.322***
N225	−0.442	−0.062	0.041***	0.256***	0.279***
OSEAX	−0.393*	−0.037	0.292**	0.317***	0.558**
OMXHPI	−0.368**	0.066	0.122	0.275**	0.246*
OMXSPI	−0.339**	0.127	0.255	0.334	0.110
AEX	−0.341**	−0.040	0.272	0.402**	0.363*
STOXX50	−0.467*	−0.122	0.193*	0.324***	0.350*
SSMI	−0.278	−0.099	0.152***	0.430***	0.364
OMXC20	−0.163**	0.185	0.109	0.123	0.037
HSI	−0.407	0.068***	0.361***	0.306***	0.369
KS11	−0.133***	0.315**	0.508	0.343	0.302
BFX	−0.467	−0.122	0.227***	0.328***	0.359***
AORD	−0.507**	−0.031	0.328**	0.496***	0.596
BVSP	−0.216**	0.219	0.430**	0.166***	0.271
NSEI	−0.390	0.040	0.286	0.330	0.294
KSE	−0.165***	0.271***	0.506***	0.445***	0.297***
MXX	−0.294	0.153***	0.591***	0.526	0.452*
SSEC	−0.311	−0.070	−0.142	−0.065	−0.238
BSESN	−0.411	0.004	0.242	0.289	0.268
GSPTSE	−0.483	−0.088	0.237	0.323	0.417
			Panel B: control = local VRP		
SP	−0.224***	0.214	0.374	0.453*	0.364
DJI	−0.159***	0.286**	0.340***	0.449***	0.503***
Nasdaq	0.053***	0.403	0.281**	0.259	−0.112
FTSE	−0.109**	0.092	0.416***	0.539	0.527
FTMIB	−0.082	−0.133	−0.249**	−0.332*	−0 .344
GDAXI	−0.216	0.236	0.270	0.478	0.557***
SSMI	−0.005**	0.216**	0.283	0.435*	0.373**
STOXX50	−0.206	0.123***	0.410***	0.405	0.212*
HSI	0.331	0.365	0.018**	−0.178***	−0.121*
N225	0.039	0.056	−0.048	0.066**	0.057*
AORD	−0.229*	0.199***	0.387***	0.492	0.309

Notes: Estimated slope coefficients in the return predictive regression (12) with X_t equal to the US VRP (Panel A) or the local VRP (Panel B). *, ** and *** denote 10-, 5- and 1-percent statistical significance using the IVX-Wald test of Kostakis et al. (2015).