The U.S. Dollar and Variance Risk Premia Imbalances*

Mads Markvart Kjær[†] Anders Merrild Posselt[‡]

*The authors were partially funded by a grant from the Danish Council for Independent Research (DFF - 0133-00151B). We thank Söhnke M. Bartram (discussant), Martijn Boons, Zhi Da, Joost Driesen, Shiyang Huang, Juan M. Londono, Andrea Vedolin and participants at the 2022 Asian Finance Association Annual Meeting at the Hong Kong Polythechnic University, the 2022 International conference of the French Finance Association at Rennes School of Business, the 2022 International conference in Quantitative Finance and Financial Econometrics at Aix-Marseille School of Economics, and seminar participants at Aarhus University for many constructive comments and suggestions.

[†]CREATES, Department of Economics and Business Economics, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark, and the Danish Finance Institute (DFI). Email: mads.markvart@econ.au.dk.

[‡]CREATES, Department of Economics and Business Economics, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark, and the Danish Finance Institute (DFI). Email: amp@econ.au.dk.

The U.S. Dollar and Variance Risk Premia Imbalances

Abstract

We present a novel predictor for the Dollar factor: variance risk premia imbalances (VPI), defined as the difference in variance risk premium in the U.S. and non-U.S. countries. We argue that VPI theoretically proxies the difference in volatility between U.S. and non-U.S. stochastic discount factors. VPI significantly predicts monthly U.S. dollar movements, explains roughly 10% of next-month Dollar factor variation, and generates significant economic value for investors. The predictive power of VPI is consistent with demand for U.S. safe assets driving dollar appreciations. We rationalize the predictability in a consumption-based framework.

Keywords: Currency return predictability, the U.S. Dollar, variance risk premium

JEL Classification: G12, G15, F31, F37

This version: October 7, 2022

1. Introduction

The U.S. Dollar (dollar) has a dominant position in the international financial markets. About 50% of cross boarder loans, international debt secutrities, and trade invoicing are dollar-denominated, while the dollar captures more than 80% of all foreign exchange transaction volume (Davies and Kent, 2020). Within currency markets, the Dollar factor serves as the most important driver of exchange rate movements (Lustig et al., 2011, 2014) and prices the cross-section of currency risk premia (Verdelhan, 2018). Yet, time-series predictability of the Dollar factor has received little attention in the literature - especially at short forecasting horizons. Our paper provides new empirical evidence for the Dollar factor being predictable at a monthly horizon. We introduce a novel predictor of the Dollar factor, variance risk premia imbalances (VPI), defined as the difference between the variance risk premium, in the U.S. and the average variance risk premium across non-U.S countries. A one-standard-deviation increase in VPI predicts a next-month Dollar factor increase of 0.68 to 0.74 percentage points with t-statistics between 3.5 to 4 and R^2s from 9.41% to 11.37%, depending on the currency basket. The gains in predictability are economically exploitable to investors - both for currency investing and hedging.

The variance risk premium (VP) is formally defined as the as the difference between the risk-neutral and physical expectation of the stock return variation. VP measures the expected cost of hedging variance risk and has different theoretical interpretations. For instance, several studies interpret VP as a measure of risk aversion (Bakshi and Kapadia, 2003, Bakshi and Madan, 2006, Bollerslev et al., 2011) others volatility of consumption volatility (Bollerslev et al., 2009, Londono, 2015, Londono and Zhou, 2017). Both interpretations indicate a link to the risk compensation required by investors or equivalently volatility of the stochastic discount factor (SDF). This implies that VPI, theoretically, proxies the difference between U.S. and non-U.S. SDF volatility. To motivate the link between VPI and exchange rates, consider, for instance, the asset market view of exchange rates (Backus et al., 2001): by no-arbitrage the exchange rate is given as the ratio between the foreign and domestic SDFs. The definition implies that short-term log exchange rate dynamics has two components: the difference in interest rates and the difference in SDF volatility. The no-arbitrage condition implies three testable hypothesis about the predictive relationship between VPI and the Dollar factor. First, the predictive VPI coefficient should be positive such that the dollar is expected to appreciate when non-U.S SDF volatility is higher than the U.S. counterpart. Second, the predictive relationship holds for both spot rate changes and excess returns. Third, the U.S. and non-U.S. VP coefficients should have opposite signs. Our results confirm all three hypotheses.

The dollar plays a central role in the factor structure of currencies. For instance, Lustig et al. (2011) find a 99% correlation between the Dollar factor and the first principal component of currencies. This implies that predictability of the Dollar factor should spill-over to predictability of bilateral exchange rates. Our empirical analysis confirms this spill-over effect: VPI has a positive coefficient for 32 and is highly significant for 28 of the 34 currencies in our cross-section. The average R^2 is 7.02% on a monthly frequency which confirms the predictive power of VPI for bilateral exchange rates. Our findings highlight the importance of the common factor structure (Lustig et al., 2011, Verdelhan, 2018) when examining time series predictability of bilateral exchange rates. Our analysis, thereby, helps understanding the exchange rate discount puzzle (Frankel and Rose, 1995).

The central position of dollar implies that the Dollar factor is the main currency risk factor in international portfolios. For VPI to improve investment decisions, the in-sample predictability must carry over out-of-sample which is not necessarily the case (e.g., Rossi, 2013). The predictive power of VPI on the Dollar factor is preserved out-of-sample, with an out-of-sample R^2 (Campbell and Thompson, 2008) of 10.97% (12.51%) relative to a random walk (with drift). We propose a simple timing strategy to utilize our findings:

the investor buys (sells) the Dollar factor whenever VPI is positive (negative). This strategy delivers significant excess returns and Sharpe ratios, even when adjusting for the two-factor model of Lustig et al. (2011) and the dollar carry strategy of Lustig et al. (2014). The timing strategy can be accommodated to hedging currency risk for which an international investor obtains sizeable economic gains.

A growing literature has focused on the role of the U.S. as the global supplier of safe assets (e.g., Krishnamurthy and Vissing-Jorgensen, 2012, Gourinchas et al., 2017, Maggiori, 2017, He et al., 2019) with potential spill-overs to the currency market. For instance, Jiang et al. (2021) show that the dollar appreciates contemporanously with increases in demand for U.S. safe assets, measured by CIP violations. We document empirically that a decline in VPI predicts an increase in safe asset demand, suggesting that future demand for U.S. safe assets increases with relative increases in non-U.S. SDF volatility. The predictive power of VPI on the Dollar factor is, hence, consistent with safe asset demand driving dollar movements.

To rationalize the predictability more formally, we modify the no-arbitrage consumption-based model of, among others, Bollerslev et al. (2009), Londono (2015), and Londono and Zhou (2017). The model rationalizes the predictability of the Dollar factor by VPI, with model-implied predictability patterns in line with the empirical evidence. Our model relies on the dominant position of the U.S. in international financial markets (e.g., Rapach et al., 2013, Miranda-Agrippino and Rey, 2020) by decomposing non-U.S. volatility of consumption volatility into a U.S. and an idiosyncratic component. This allows VPs to correlate across countries with the model-implied predictive power of VPI being decreasing in the correlation between U.S. and non-U.S. VPs. In the extreme case of perfect correlation, the SDF volatility is identical across countries implying that VPI contains no predictive information on exchange rate movements. The model rationalizes the predictive power of both U.S. and non-U.S. VPs on the Dollar factor unless the VPs are perfectly correlated across countries.

The remainder of the paper is organized as follows. Section 2 summarizes the related literature. Section 3 provides a heuristic theoretical motivation. Section 4 describes the data. Section 5 presents in-sample results. Section 6 shows that the predictability is preserved out-of-sample. Section 7 shows the linkage to safe asset demand. Section 8 elaborates on the theoretical rationalization in a consumption-based framework while Section 9 concludes.

2. Related literature

Going back to Meese and Rogoff (1983), a long-standing issue in international finance is the difficulties of predicting exchange rate movements using economic fundamentals - also known as the exchange rate disconnect puzzle. Froot and Rogoff (1995), Frankel and Rose (1995), and Engel and West (2005) all find that exchange rate movements are disconnected from economic fundamentals at short forecast horizons. However, at longer horizons, studies have shown evidence of predictability. For instance, focusing on the Dollar factor, Lustig et al. (2014) considers the average forward discount while Jiang (2021) considers the U.S. debt capacity as predictor. Our paper shows that exchange rate movements are predictable at short horizons.

A separate literature considers the special role of the dollar in international financial markets. Lustig et al. (2011) and Lustig et al. (2014) find that a global Dollar factor serves as the most important driver of exchange rate movements and drives currency returns around the world. Verdelhan (2018) present evidence that exposure towards the Dollar factor drives currency returns in the cross-section. Our results highlight that the factor structure in currencies can be utilized in time series predictions: predictability of the Dollar factor has a direct spill-over to bilateral exchange rates.

We are not the first to examine the information in variance risk premia about currency returns. Focusing on information from currency options, Della Corte et al. (2016) find that the individual volatility risk premium is significant in cross-sectional predictability. In the time series dimension, Londono and Zhou (2017) find that a global average of variance risk premia from currency options predicts bilateral exchange rates. Focusing on stock options, they also show that the U.S. variance risk premium contains predictive information on currency returns, indicating an information spillover from stock markets to currency markets. Fan et al. (2022) find that an option-based equity tail risk factor is priced in the cross section of currency returns. As currencies theoretically involve the SDFs from two countries, a natural extension is to also consider the non-U.S. variance risk premium. Our paper contributes to this literature by documenting the importance of the non-U.S. component when modelling expected currency returns.

Last, our paper is related to an emerging literature on the special role of the U.S. as the global supplier of safe assets (e.g., Krishnamurthy and Vissing-Jorgensen, 2012, Gourinchas et al., 2017, Maggiori, 2017, He et al., 2019). Both Du et al. (2018) and Jiang et al. (2021) attribute deviations from the covered interest rate parity (CIP) to a convenience yield driven by safe asset demand for U.S. Treasuries. Our empiricial results support the view that safe asset demand drives dollar movements by showing that VPI predicts the demand for U.S. safe assets.

3. Variance risk premia imbalances and the Dollar factor

This section introduces a new predictor for the Dollar factor, variance risk premia imbalances (VPI). Even though our contribution is mainly empirical, we provide a heuristic theoretical motivation of VPI based on the asset market view of exchange rates. In Section 8, we elaborate on the theoretical link in a specific no-arbitrage consumption-based model.

3.1. Variance risk premia imbalances

We define the variance risk premia imbalance (VPI) as the difference between the U.S. variance risk premium and the average variance risk premia for a cross-secion of non-U.S. countries ($\overline{VP}_t$):

$$VPI_t = VP_{US,t} - \overline{VP}_t \tag{1}$$

$$\overline{VP}_t = \frac{1}{N}\sum_{i}^{N} VP_{i,t} \; \forall i \neq US,$$

where $VP_{i,t}$ is the variance risk premium in country i given as:

$$VP_{i,t} \equiv E_t^{\mathbb{Q}_i}(\sigma^2_{i,t,t+1}) - E_t^{\mathbb{P}}(\sigma^2_{i,t,t+1}). \tag{2}$$

$\mathbb{Q}$ ($\mathbb{P}$) denotes the risk-neutral (physical) measure, and $\sigma_{i,t,t+1}$ is the country i, stock market return volatility from t to $t+1$. To estimate $\mathbb{Q}$ and $\mathbb{P}$ expectations, we follow among others Bollerslev et al. (2009), Della Corte et al. (2016) and Londono and Zhou (2017), and consider the (model-free) option-implied variance and the realized variance for the past 22 trading days, respectively.

The variance risk premium (VP) is the expected cost of entering a long position in a variance swap and measures the investors willingness to pay for hedging variance risk (Bakshi and Kapadia, 2003, Carr and Wu, 2009, Bollerslev et al., 2009, Bekaert and Hoerova, 2014, Londono, 2015). Several studies suggest that VP also has a more fundamental theoretical interpretation. For instance, Bakshi and Kapadia (2003), Bakshi and Madan (2006), and Bollerslev et al. (2011) shows that VP proxies relative risk aversion, while Bollerslev et al. (2009) propose a model in which VP is a risk premium for volatility of consumption-volatility. Both interpretations suggest a link to the risk compensation required by investors and thereby SDF volatility. Following this intuition, VPI proxies the average difference in SDF volatility between U.S. and non-U.S countries.

3.2. Theoretical motivation

To motivate the predictive ability of VPI on the Dollar factor, we depart from the asset market view of exchange rates, i.e., under no-arbitrage, each exchange rate (relative to the dollar) is determined by the ratio between the foreign and U.S. SDFs (e.g., Backus et al., 2001):

$$\frac{\tilde{M}(T)}{M(T)} = \frac{S(T)}{S(t)}, \tag{3}$$

$$\frac{d\tilde{M}(T)}{\tilde{M}(T)} = -\tilde{r}_T dt - \tilde{\lambda}_T dW_t, \tag{4}$$

$$\frac{dM(T)}{M(T)} = -r_T dt - \lambda_T dW_t, \tag{5}$$

where $M(t)$ ($\tilde{M}(t)$) denotes the U.S. (foreign) SDF, r ($\tilde{r}$) denotes the risk-free rate, λ ($\tilde{\lambda}$) the SDF volatility, W_t is a Brownian motion, and $S(t)$ is the exchange rate measured as dollar per unit of foreign currency.

By applying Itô's lemma, the log exchange rate has the following dynamics:

$$ds_t = (r_t - \tilde{r}_t + \frac{1}{2}(\lambda_t'\lambda_t - \tilde{\lambda}_t'\tilde{\lambda}_t))dt + (\lambda_t - \tilde{\lambda}_t)dW_t. \tag{6}$$

Given that the Dollar factor is given as a cross-sectional average of changes across currencies, the dynamics of the Dollar factor is:

$$d\bar{s}_t = (r_t - \bar{r}_t + \frac{1}{2}(\lambda_t'\lambda_t - \bar{\lambda}_t'\bar{\lambda}_t))dt + (\lambda_t - \bar{\lambda}_t)dW_t, \tag{7}$$

where $\bar{r}$ and $\bar{\lambda}$ denote a cross-sectional average of the foreign short interest rate and SDF volatility, respectively. An Euler-discretization of Equation (7) shows that expected short-term Dollar factor movements has two components: the average difference in interest rates and the average difference in the SDF volatility. The economic interpretation of VP suggests that VPI proxies the latter.

To explain the intuition of the theory, consider the case of one single risk factor, $\check{W}_t$, and let both the U.S. and non-U.S. stock indices have equal positive exposure to the risk factor. If U.S. investors require higher compensation for the risk factor exposure relative to non-U.S. investors, an arbitrage oppotunity exists unless the exchange rate reflects the difference in risk compensation.[1] In this case, Equation (3) predicts the dollar to depreciate. Note that the hypothesis is a common prediction for the class of models derived from Equation (3).

Combining the economic interpretation of VPI with the asset market view of exchange rates, generates the following testable hypotheses:

Hypothesis 1: VPI has predictive power of the Dollar factor with a positive predictive slope coefficient.

Hypothesis 2: VPI has predictive power for both excess returns and spot rate changes.

Hypothesis 3: U.S. VP has a positive predictive slope coefficient and non-U.S. has a negative predictive slope coefficient.

4. Data

This section describes the data. The data are; returns on the main stock indicies in a cross-section of countries, their option implied volatility index, and spot- and forward

[1] The arbitrage strategy is to buy the U.S. stock index and sell the rest of the world such that they have zero exposure towards the risk factor.

exchange rates.

4.1. VPI

To construct VPI, we consider the headline stock index of G10 countries with available option-implied stock volatility index; Australia, Canada, France, Germany, Italy, Japan, Netherlands, Switzerland, United Kingdom, and the United States. We construct a Euro VP as the GDP weighted average of the VPs available for the Eurozone countries.[2] Daily index prices and option-implied volatility indices are sourced from Bloomberg, and we calculate VPI using end-of-month observations following Equation (1). The sample spans from January 2000 to the end of December 2019 with the starting point selected because of data availability. Table 1 reports summary statistics of VPI along with summary statistics and correlations for the country-specific VPs.

TABLE 1 ABOUT HERE

The country VPs are highly correlated with an average correlation of 0.52. The correlation is highest between U.S. and U.K. (0.82) and lowest between Japan and Euro (0.19). The average and median VP are both positive for all countries, highest for Japan, lowest for Switzerland. The Japanese VP, furthermore, has the highest standard deviation while U.S. has the second-highest (317.51% and 311.26% respectively). For all countries, the VP deviates substantially from the normal distribution, with a rather high kurtosis and negative skewness (except Australia). VPI is negative on average (-0.97) but has a positive median of 11.15 with a standard deviation of 197.10%. VPI is negatively skewed and has a high kurtosis. Figure 1 plots VPI.

FIGURE 1 ABOUT HERE

[2] Our predictive results are qualitatively and quantitatively the same if we had replaced the Euro VP measure with VP on the Euro Stoxx 50 index.

In particular, we note the sharp declines in 2008 (the collapse of Lehman Brothers) and 2011 (the Southern European debt crisis). Although the time series overall appear to be stationary, the suppressed level during the financial crisis is quite persistent. However, in unreported results, we reject the null hypothesis of a unit root at the 1% significance level.

4.2. Currency data

We consider daily spot and forward exchange rates spanning from January 2000 to the end of December 2019 measured in dollar per unit of foreign currency obtained from Thomson Reuters. We construct monthly (end-of-month) log spot changes and excess returns as:

$$\Delta s_{t,i} = s_{t,i} - s_{t-1,i}, \tag{8}$$

$$rx_{t,i} = s_{t,i} - f_{t-1,t,i}, \tag{9}$$

where s_t denotes the log currency spot rate at time t, $f_{t-1,t}$ denotes the time $t-1$ one-month log forward exchange rate with expiration at time t. The excess return is given as the return of buying a one-month forward contract today and selling the spot rate at delivery.

Our main dataset consists of exchange rates for the following cross-section of countries: *Australia*, Brazil, Bulgaria, *Canada*, Croatia, Czech Republic, Cyprus, *Denmark*, Egypt, Hungary, Iceland, India, Israel, *Japan*, Kuwait, Malaysia, Mexico, *New Zealand*, *Norway*, Philippines, Poland, Russia, Slovakia, Singapore, South Africa, South Korea, *Sweden*, *Switzerland*, Taiwan, Thailand, Ukraine, *United Kingdom*, and lastly the *Euro*. We divide the cross-section into three currency baskets: Developed, Emerging, and All. Developed is defined in italic above, Emerging is the rest, and All is all countries.

In accordance with Lustig et al. (2014), we exclude dollar-pegged currencies (Saudi Arabia and Hongkong) and currencies for which we observe large CIP deviations, typically a sign of illiquidity in the forward contracts. These we observe for South Africa (January 2002 to May 2005), Malaysia (start of the sample to June 2005), Indonesia (December 2000 to May 2007), Egypt (November 2011 to August 2013, and again from September 2016 and onwards), and Ukraine (January 2014 to end of sample).

Next, we define the Dollar factor as a long position in the cross-section of currencies for currency basket, j, and a short position in the dollar - both in terms of excess returns (excess Dollar factor, $\overline{rx}_{t,j}$) and spot rate changes (spot Dollar factor, $\overline{s}_{t,j}$):

$$\overline{rx}_{t,j} = \frac{1}{N_j} \sum_{i=1}^{N_j} rx_{t,i}, \tag{10}$$

$$\overline{\Delta s}_{t,j} = \frac{1}{N_j} \sum_{i=1}^{N_j} \Delta s_{t,i}, \tag{11}$$

where N_j is the number of currencies in currency basket j. A positive excess (spot) Dollar factor corresponds to an average positive excess return (appreciation) of the currency basket relative to the the dollar. In the remainder of the paper, the Dollar factor refers to both the excess and spot versions. Our definition of the Dollar factor is slightly different from Lustig et al. (2011), in which the Dollar factor is defined as a cross-sectional average of Carry portfolios. All the results remain using this definition.

5. Dollar factor predictability and VPI

This section investigates the three theoretical hypotheses empirically. We begin by showing that VPI is a strong predictor of the Dollar factor for all currency baskets. Next, we split VPI into the two components, U.S. and non-U.S. and show that both coefficients are significant with opposite sign, confirming Hypothesis 3. We also show that the gains in predictability carry over to bilateral exchange rates. Last, we show that the predictive power of VPI preserves when controlling existing currency predictors (Lustig et al., 2014, Londono and Zhou, 2017) and global risk (Miranda-Agrippino and Rey, 2020).

5.1. Predictability tests

In the first analysis, we explore the in-sample predictability of the Dollar factor by VPI. For each currency basket, j, we run the following two non-overlapping predictive regressions of VPI on the next-month Dollar factor, $\overline{\Delta s}_{t+1,j}$ and $\overline{rx}_{t+1,j}$:

$$\overline{\Delta s}_{t+1,j} = b_0 + b_{VPI} VPI_t + \eta_{t+1}, \tag{12}$$

$$\overline{rx}_{t+1,j} = \beta_0 + \beta_{VPI} VPI_t + \varepsilon_{t+1}, \tag{13}$$

For ease of interpretation, we standardize VPI. Table 2 presents the estimated b- and β coefficients for the different currency baskets along with t-statistics (in brackets).

Table 2 about here

The coefficients on VPI are all large and positive with t-statistics above 3.50. Focusing on the excess returns (Panel A) for the Developed basket, a one standard deviation increase in VPI predicts an 0.74 percentage point increase in the Dollar factor (8.88 percentage points annualized). The coefficients are slightly smaller for the other baskets: 0.62 and 0.63 (7.44 and 7.56 annualized) for Emerging and All, respectively. The implication is; an increase (decrease) in the U.S. VP relative to the average non-U.S. VP, predicts an increase in the average excess returns of the currency basket relative to the dollar. VPI explains a large share of next-month Dollar factor variations with R^2s between 9.71% and 10.72%. The results are almost identical for spot rate changes (Panel B) confirming that VPI predicts risk premia and not the interest rate difference.

Next, we split VPI into U.S. and non-U.S. components. If VPI proxies the difference in SDF volatility between U.S. and non-U.S., the U.S. coeffcient should be positive and the non-U.S. negative. To examine the hypothesis, we regress the next-month excess returns and spot rate changes on the two components. Table 3 presents the coefficients (t-statistics in brackets) and a Wald test for equal absolute coefficients (p-values in parenthesis). For comparability of the coefficents, we do not standardize the variables.

Table 3 about here

Across all baskets, the coefficients on both components are statistically significant, with opposite sign and similar magnitude. Consistent with our theoretical motivation, the U.S. coefficient is positive while the non-U.S. is negative. For the All and Developed baskets, we cannot reject that the U.S. and non-U.S. coefficients are equal in absolute terms while the tests are borderline significant for Emerging. Our findings are consistent with Londono and Zhou (2017) who document that the U.S. VP predicts the Dollar factor. Nevertheless, our analysis also shows that the non-U.S. component is important for understanding currency risk premium.

Our empirical analysis confirm Hypothesis 1-3, across all currency baskets, and are consistent with VPI proxying the difference in U.S. and non-U.S. SDF volatility. When non-U.S. SDF volatility is higher than U.S. (VPI is negative), expected dollar returns are positive.

5.2. Longer horizon returns

So far, we have focused on one-month returns and have not examined longer horizons. Table 4 presents the results based on 2-, 3-, 6-, 9-, and 12-month overlapping returns.

Table 4 about here

The coefficient on VPI is diminishing as the return horizon increases and even switches sign at the longest forecast horizon. The VPI coefficient is significant for 2-months returns, mixed results for 3-months returns, and insignificant for any longer horizons. Given that the return horizon is different, we cannot compare the coefficients without an annualization. Figure 2 presents the annualized coefficients.

Figure 2 about here

The annualized coefficient is monotonically decreasing in the return horizon. The evidence suggest that the predictive power of VPI is relatively short-lived.

5.3. VPI and bilateral exchange rates

We now examine whether predictability for the Dollar factor carries over to predictability for individual currencies. The common factor structure in currencies (Lustig et al., 2011) suggets that VPI predicts bilateral exchange rates by capturing the Dollar risk premium. We examine the hypothesis by, first, running a panel regression of the bilateral exchange rates on VPI and, second, seperate individual predictive regressions (currency-by-currency). The panel regressions are given as:

$$\Delta s^i_{t+1} = b_{0,i} + b_{VPI} VPI_t + \hat{\varepsilon}_{t+1}, \tag{14}$$

$$rx^i_{t+1} = \beta_{0,i} + \beta_{VPI} VPI_t + \varepsilon_{t+1}, \tag{15}$$

where $b_{0,i}$ and $\beta_{0,i}$ are currency-fixed effects such that only the slope coefficients of VPI are constrained to be equal across currencies. Table 5 presents the panel regression results for the three currency baskets. The t-statistics, reported in brackets, are computed using robust standard errors clustered by month and currency.

Table 5 about here

Compared to the results for the Dollar factor, the VPI coefficients are almost identical (cf. Table 2) ranging from 0.69 to 0.74 for excess returns and 0.65 to 0.74 for spot rate changes, all highly statistically significant.

To explore the heterogeneity in the predictive power of VPI, we run individual regressions for each currency. Table 6 reports the results.

Table 6 about here

A similar picture as in the panel regression emerges from the individual predictive regressions. VPI is significant at the 1% (5%) level for 24 (28) of the 34 currencies in our sample. The average coefficient is 0.70, t-statistic is 3.32, and R^2 is 7.02%. Our results show a spill-over effect from predictability of the Dollar factor to bilateral exchange rates. The common factor structure can, thereby, be exploited for predicting individual currencies.

5.4. Controlling for existing predictors

To assess the incremental predictive power of VPI for the Dollar factor, we consider a series of existing control predictors. First, we control for the currency variance risk premium (XVP)[3] in Londono and Zhou (2017) which they show predicts bilateral exchange rates. Second, we consider the average forward discount (AFD) in Lustig et al. (2014), which they show has predictive power on the Dollar factor. Last, we control for the global financial cycle (GFC) in Miranda-Agrippino et al. (2020), which identify a global factor that explains a large share of variation in risky assets. Miranda-Agrippino et al. (2020) show a close link between GFC and U.S. monetary policy, which affects the dollar. We focus on the excess returns in the interest of space. The results are identical for the spot rate changes.

[3] We calculate the variance risk premium based on implied volatility on one-month at-the-money currency options obtained from Thomson Reuters for the same six currencies as VPI: Euro, U.K. (GBP), Japan (JPY), Australia (AUD), Canada (CAD), and Switzerland (CHF).

Table 7 presents the coeffcients, t-statistics, and R^2s, controlling for the three predictors in Equation (13).

Table 7 about here

The VPI coefficients and t-statistics are essentially unaffected by the existing predictors. Controlling for GFC even increases both the VPI coefficient and t-statistic. All control predictors are insignificant. The degree of explained variation increases a bit when including GFC, while AFD and XVP are roughly similar to Table 2. None of the existing predictors explains the predictive power of VPI.

6. Out-of-sample evidence

For VPI to improve investment decisions, the in-sample predictability must carry over out-of-sample. In this section, we show that predictability of VPI preserves for both the Dollar factor and bilateral exchange rates. We then present two examples for investors to utilize predictability: First, a simple investment strategy, taking a long or short Dollar factor position based on the sign of VPI. Second, a hedging strategy against currency exposure arising from international investments. As we take an investor perspective, we apply discrete returns instead of log returns.[4] In the interest of space, we focus on excess returns.

6.1. Out-of-sample prediction of the Dollar factor

Our previous results show that, in-sample, VPI is a strong predictor for the Dollar factor. We will now explore whether this also holds out-of-sample. Each month, we re-estimate Equation (13) using a fixed-length rolling window comprised of observations for the previous 60 months.[5] For this exercise, the Dollar factor denotes the average excess returns

[4] We find qualitatively similar results using log returns.
[5] We find qualitatively similar results using an expanding window.

of the currency basket containing developed currencies. Panel A in Table 8 reports out-of-sample R^2s (R^2_{OoS}) (Campbell and Thompson, 2008, Goyal and Welch, 2008) relative to a random walk or random walk with drift (historical average). A positive R^2_{OoS} indicates that the VPI-based model has a lower mean squared prediction error than the benchmark. In parenthesis, we provide the p-values of the Clark and West (2007) test. The null hypothesis is equal predictive ability while the alternative is that the VPI-based model is better than the benchmark.

Table 8 about here

Our results show that the dollar factor is also predictable out-of-sample. VPI delivers a sizeable R^2_{OoS} of 10.97% (12.51%) against a random walk (with drift), significantly positive at the 5% level. The magnitude of the R^2_{OoS} is large compared to existing literature (e.g., Rossi, 2013) which typically find that currencies are well described by a random walk. We note, however, the limited out-of-sample period due to the availability of data.

6.2. Bilateral out-of-sample predictions

Next, we examine out-of-sample predictability of bilateral exchange rates. First, we recursively run a contemporanous regression of the currency excess returns on the dollar factor:

$$rx_t^i = \beta_{0,i} + \beta_{DOL,i}\overline{rx}_t + \varepsilon_t. \tag{16}$$

We then insert the forecasts from Section 6.1, $\widehat{\widehat{rx}}_{t+1}$, into Equation (16) to construct the bilateral currency forecast:

$$\hat{rx}^i_{t+1} = \hat{\beta}_{0,i} + \hat{\beta}_{DOL,i}\widehat{\widehat{rx}}_{t+1}. \tag{17}$$

The constant in Equation (16) acknowledges the evidence of additional common currency factors (e.g., Lustig et al., 2011, Colacito et al., 2020) and allows for a systematic pricing error not captured by the dollar factor.[6]

In the interest of space, we focus on the cross-section of G10 currencies.[7] Panel B in Table 8 presents the R^2_{OoS} with p-values in parenthesis.[8] Since the results are very similar for the two benchmarks, we focus on the results using a random walk as benchmark.

VPI generates sizeable improvements in out-of-sample accuracy for bilateral exchange rates, consistent with our in-sample evidence. The R^2_{OoS} is highly positive for all currencies except Japan, ranging from 4.11% (Switzerland) to 12.89% (U.K.). For all but U.K. and Japan, the p-values are below 5% (U.K. is borderline significant with a p-value of 6%). The negative R^2_{OoS} for Japan is consistent with the in-sample results. The results, thereby, testify to the predictive power of VPI out-of-sample.

6.3. Investment strategy

We find so far that increases in VPI leads to increases in the next-month Dollar factor and document predictability both in and out-of-sample. We now examine whether this predictability leads to economic gains for investors. First, we propose a simple investment strategy that exploits the predictive power of VPI: buy the Dollar factor when VPI is

[6] For the G10 currency, the results are slightly better when not including the constant in Equation (16).

[7] G10 currencies relative to the dollar consist of: Australia, Canada, Euro, Japan, New Zealand, Norway, Sweden, Switzerland, and U.K.

[8] We find similar results for the rest of the cross-section - only India and Japan return negative R^2_{OS} relative to a random walk. The average R^2_{OoS} is 7.10% for the entire cross-section with the random walk as benchmark.

positive, otherwise sell. Investors thereby go long dollar when non-U.S. SDF volatility is higher than U.S., and short otherwise. We label this the VPI strategy. Conditioning on the sign of VPI is motivated by the insignificant intercept in Equation (13) and allows us to extend the evaluation period compared to the out-of-sample period in Section 6.1.

Figure 3, Panel a and b, plots the cumulative returns of the VPI strategy (blue line) along with the buy-and-hold cumulative returns of the Dollar factor (red line) for the Developed and All currency baskets. As the results for the two baskets are very similar, we only comment on the Developed basket (Panel b).

Figure 3 about here

The end-of-sample cumulative returns of the VPI strategy are well above the buy-and-hold alternative (80% against 21%), despite a period of underperformance from the start of 2002 to mid-2008. Panel c plots the cumulative return difference of the two strategies. The VPI strategy outperforms the buy-and-hold from 2008 until the end of the sample. Specifically, we note sharp increases in relative performance in 2008-2009, the second half of 2011, and 2018-2019. All periods of heightened market volatility and dollar appreciations. Hence, the VPI strategy appears to capture the increased demand for U.S. safe-assets, associated with dollar appreaciation (Jiang et al., 2021). We explore this link further in Section 7.

Table 9 reports the annualized excess returns, t-statistics, and Sharpe ratios of both the VPI and buy-and-hold strategies.

Table 9 about here

The annualized average excess returns are 4.10% (Developed) and 3.12% (All) with Sharpe ratios of 0.50 and 0.44. In comparison, the buy-and-hold strategy of the Dollar factor (see Panel B) generates average excess returns of 1.14% (Developed) and 2.01% (All) with Sharpe ratios of 0.14 (Developed) and 0.29 (All). In sum, the results show sizeable performance gains from timing the Dollar factor by VPI. Finally, in Panel C, we control for the dollar factor, the carry risk factor (HML) (Lustig et al., 2011), and the dollar carry strategy (dollar carry) (Lustig et al., 2014). The abnormal returns are close to the returns reported in Panel A with weak loadings on HML and dollar carry. Hence, the VPI strategy is not merely harvesting the risk premia associated with carry strategies.

6.4. Hedging strategy

Next, we accommodate the VPI strategy to hedging currency exposure arising from international investments. Concretely, we explore the economic gains for a U.S.-based investor holding a portfolio of foreign stocks. The portfolio incurs a foreign exchange rate exposure which she can hedge using forward contracts. In line with the VPI strategy, the hedging strategy is: if VPI is negative hedge currency risk, otherwise do not hedge. The hedge position is an equal-weighted position in the forward contracts. For this exercise, we consider a similar scenario as Opie and Riddiough (2020); the investor has an equal-weighted long position in the MSCI indices of the G10 currencies,[9] excluding the U.S. stock market. We label the hedge strategy as the VPI portfolio. We consider two benchmark portfolios: an unhedged and a fully hedged portfolio. Using monthly rebalancing, we evaluate the out-of-sample portfolio performance by the Sharpe ratio, Sortino ratio, certainty equivalence, and performance fee.[10] Table 10 presents the annualized results.[11]

Table 10 about here

The VPI portfolio delivers a higher average return (roughly 1.3% and 2.4% in excess), Sharpe- and Sortino ratio than both the unhedged and fully hedged portfolio. The

[9]Sourced from Bloomberg.

[10]The fee a mean-variance investor is willing to pay to switch from a benchmark portfolio to the VPI portfolio

[11]In the presented results, we do not take transaction costs into account. However, un-reported results show that incorporating bid-ask spreads results are substantially unchanged.

certainty equivalence is also higher, and an investor with mean-variance preferences is willing to pay between 150 and 210 annual basis points for switching from the benchmarks to the VPI portfolio. The superior performance is obtained without negatively impacting higher-order moments, as the VPI portfolio has the least negative skewness and a lower kurtosis.

For further comparison Figure 4, Panel (a) shows the cumulative return paths for each portfolio.

FIGURE 4 ABOUT HERE

The end-of-sample cumulative return of the VPI portfolio is substantially above the benchmarks (126% against 100% and 78%). Panel (b) plots the cumulative return difference between the VPI portfolio and the two benchmarks separately. For the unhedged portfolio, the higher returns of the VPI portfolio are mainly generated from 2008 and onwards, benefiting from several dollar appreciations. Comparing with the full-hedge portfolio, the gains of the VPI portfolio are generated in the period from 2002 to mid-2014. Our results indicate that in the context of hedging currency risk, exploiting the predictive power of VPI generates sizeable gains.

7. VPI and safe asset demand

Our empirical results show that VPI contains powerfull predictive information on future Dollar factor returns and, thereby, confirms the theoretically motivated hypotheses that VPI proxies the difference between U.S. and non-U.S. SDF volatility. A growing literature has focused on the role of the U.S. as the global supplier of safe assets (e.g., Krishnamurthy and Vissing-Jorgensen, 2012, Gourinchas et al., 2017, Maggiori, 2017, He et al., 2019) with the demand for safe assets being a potential driver of dollar movements (Jiang et al., 2021). In this section, we show that VPI predicts demand for U.S. safe assets.

Increases in non-U.S. SDF volatility relative to U.S., predict increases in demand for U.S. safe assets. The predictive power of VPI on the dollar factor is thereby consistent with demand for U.S. safe assets driving the dollar. We proxy demand for U.S. safe assets by convenience yields and explicit buy-side demand for U.S. Treasuries.

7.1. VPI and convenience yields

First, we consider the relation between VPI and convenience yields. Both Du et al. (2018) and Jiang et al. (2021) attribute the CIP violations in government bond markets to convenience yields driven by safe asset demand meaning that convenience yields proxy safe asset demand.

To measure convenience yields, we consider the U.S. Treasury basis, x_t, defined as the difference between a U.S. yield and a currency-hedged non-U.S. yield. A negative basis means that U.S. Treasuries are expensive relative to the non-U.S counterpart implying that non-U.S. investors are willing to pay a premium for holding U.S. safe assets. We investigate the link between global demand for U.S. safe assets and VPI by the following predictive regression:

$$\bar{x}_{t+1} = \delta_0 + \delta_{VPI} VPI_t + \epsilon_{t+1}, \tag{18}$$

where $\bar{x}_t$ is a cross-sectional average of U.S. Treasury bases across the same six countries as VPI.

In the model of Jiang et al. (2021), non-U.S. investors receive lower expected returns (in their own currencies) for holding U.S. safe assets when increasing their valuation of the current and future convenience properties of U.S. safe assets. To produce lower future expected returns, the dollar must appreciate today and, in expectation, depreciate in the future. If the predictive power of VPI is consistent with the theory of Jiang et al. (2021), the VPI coefficient in Equation (18) should be negative.

We consider, on a monthly frequency, the bases of 1-year Treasuries[12] and 1-year interbank rates.[13] Panel A in Table 11 presents the results.

TABLE 11 ABOUT HERE

Consistent with the theory of Jiang et al. (2021), an increase in VPI predicts a decline in the demand for U.S. safe assets. The regression coefficients are significantly negative - both economically and stastically with notable degress of explained variation. An one-standard deviation increase in VPI predicts a decline of 6.35 basis points in the U.S. Treasury basis with a R^2 of 17.49%. For the Interbank rates, the expected decline is 3.42 basis points and the R^2 is 4.63%. The results imply a substantial part of the variation in the premium that non-U.S. investors are willing to pay for holding U.S. safe assets can be predicted by VPI. Our analysis suggests that increases in non-U.S. SDF volatility relative to U.S. predict increases in the demand for U.S. safe assets leading to dollar appreciations.

7.2. VPI and buy-side safe asset demand

We turn now to an alternative proxy for safe asset demand. In particular, we consider the difference in long and short open interest on U.S. Treasury futures contracts for buy-side investors and examine the following predictive regression:

$$log(OI_{t+1}^{long}) - log(OI_{t+1}^{short}) = \psi_0 + \psi_{VPI} VPI_t + \epsilon_{t+1}, \tag{19}$$

where OI_{t+1}^{long} is the open interest of long positions in the safe asset while OI_{t+1}^{short} is the open interest of short positions.

[12]Obtained from Du et al. (2018) and available here: https://sites.google.com/view/jschreger/CIP?authuser=0

[13]The ibor rates are obtained from Global Financial Data

Given the positive predictive relationship between VPI and the Dollar factor, a safe asset demand explanation of VPIs predictability implies a negative coefficient in Equation (19). We obtain open interests from the CFTC Traders in Financial Futures (TFF) report and define buy-side investors as the categories "Asset Managers"[14] and "Leveraged Funds".[15] We consider the 2-year Treasury, 5-year Treasury, 10-year Treasury, and U.S. bond Treasury futures. The TFF report is published on a weekly basis so we consider a weekly frequency to estimate Equation (19). Panel B of Tabel 11 presents the results with open interest aggregated the different interest rate futures.

Consistent with the analysis on CIP violations, the VPI coefficient is significantly negative. A one-standard deviation decrease in VPI predicts that buy-side investors increase their net position in U.S. Treasury futures by 3%. Hence, buy-side investors increase their demand for U.S. safe assets following a relative increase in non-U.S. SDF volatility.

8. A model with correlated variance risk premia

Section 3 provided a heuristic theoretical argument for the relation between VPI and the Dollar factor. The following section elaborates on the theoretical link by considering VPI and the Dollar factor in an international consumption-based asset pricing model. We extend the model of Londono and Zhou (2017) by allowing for VP correlations to vary across countries, cf. Table 1. For each non-U.S. country, volatility of nominal consumption growth uncertainty (vol-of-vol) consists of an idiosyncratic and a U.S. component. This assumption is consistent with Rapach et al. (2013) and Miranda-Agrippino and Rey

[14]This category includes pension funds, endowments, insurance companies, mutual funds, and those investment managers whose clients are predominantly institutional. Explanatory notes of the report can be found at; https://www.cftc.gov/sites/default/files/idc/groups/public/@commitmentsoftraders/documents/file/tfmexplanatorynotes.pdf

[15]This category includes; hedge funds, various types of money managers and commodity trading advisors.

(2020), who find that the U.S. has a leading role in international financial markets. The dependence on U.S. vol-of-vol may differ across non-U.S. countries, which allows the correlations of country VPs to vary across countries. The model-implied VPI is decreasing in the average idiosyncratic vol-of-vol across non-U.S. countries and increasing in U.S. vol-of-vol. Similarly, the Dollar factor is depreciating in the average non-U.S. idiosyncratic vol-of-vol, and appreciating in U.S. vol-of-vol. Hence, the model implies positive predictive relationship between VPI and the Dollar factor. The first part of this section introduces the model and the second part presents the model-implied predictability of VPI on the Dollar factor.

8.1. The model

Our model modifies the framework of Londono and Zhou (2017) who extends the domestic framework of Bollerslev et al. (2009). For country i, nominal consumption growth is governed by the process:

$$g_{i,t+1} = \mu_i + \phi_{g,i}\sigma_{i,t}z_{g,i,t+1}, \tag{20}$$

where μ_i denotes the constant mean growth rate, $\sigma_{i,t+1}$ is the volatility of the growth rate and $z_{g,i,t+1}$ is an N(0,1) i.i.d. process. $\sigma_{i,t}$ is assumed to follow the square root process:

$$\sigma^2_{i,t+1} = \mu_{\sigma,i} + \rho_{\sigma,i}\sigma^2_{i,t} + \phi_{\sigma,i}\sqrt{q_{i,t}}z_{\sigma,i,t+1}, \tag{21}$$

where,

$$q_{i,t+1} = \omega_i\bar{q}_{t+1} + (1-\omega_i)\tilde{q}_{i,t+1}, \tag{22}$$

$$\tilde{q}_{i,t+1} = \mu_{\tilde{q},i} + \tilde{\rho}_i\tilde{q}_{i,t} + \phi_{\tilde{q},i}\sqrt{\tilde{q}_{i,t}}z_{\tilde{q},i,t+1}, \tag{23}$$

$$\bar{q}_{t+1} = \mu_{\bar{q}} + \bar{\rho}\bar{q}_t + \phi_{\bar{q}}\sqrt{\bar{q}_t}z_{\bar{q},t+1}. \tag{24}$$

For each country, the volatility of consumption-volatility (vol-of-vol), $q_{i,t}$, is a weighted average of a country specific component, $\tilde{q}_{i,t}$, and a U.S. component $\bar{q}_t$. Both are governed by a square-root process. We impose $\omega_i = 1$ for the U.S. vol-of-vol. To simplify notation, we drop the subscript for U.S. and refer to non-U.S. countries with subscript i. All conditions and assumptions will apply to both the U.S. and non-U.S. countries.

For all countries, the parameters satisfy that $\mu_{\tilde{q},i} > 0$, $\mu_{\bar{q}} > 0$, $0 < \omega_i < 1$, $\tilde{\rho}_i < 1$, $\bar{\rho} < 1$, $\phi_{\tilde{q},i} > 0$, $\phi_{\bar{q}} > 0$, while $z_{\sigma,i,t+1}$, $z_{\tilde{q},i,t+1}$, and $z_{\bar{q},t+1}$ are i.i.d. N(0,1) processes. In each country, we assume the representative agent has recursive preferences of Epstein and Zin (1989) and Weil (1989) implying the following SDF, m_i:

$$m_{i,t+1} = \theta \log(\delta) - \frac{\theta}{\psi} g_{i,t+1} + (\theta - 1) r_{i,t+1}, \tag{25}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, ψ is the intertemporal elasticity of substitution, γ is the coefficient of risk aversion, $r_{i,t}$ is the return of an asset paying the country i's consumption as dividends, and $0 < \delta < 1$ is the time discount factor. We follow Bollerslev et al. (2009) and assume that $\gamma > 1$ and $\psi > 1$ which leads to $\theta < 0$, ensuring that volatility carries a positive risk premium. For simplicity, we assume that the parameters of the utility function are homogenous across all countries.

Let z_t denote the log price-dividend ratio (equivalently the wealth-consumption ratio). The model is then solved in a standard fashion by applying the Campbell and Shiller (1988a) log-linearization of returns:

$$r_{i,t+1} = \kappa_0 + \kappa_1 z_{i,t+1} - z_{i,t} + g_{i,t+1}, \tag{26}$$

and conjecturing that the log wealth-consumption ratio is affine in the state variables:

$$z_{i,t+1} = A_{0,i} + A_{\sigma,i}\sigma^2_{i,t+1} + A_{\tilde{q},i}(1-\omega_i)\tilde{q}_{i,t+1} + A_{\bar{q},i}\omega_i\bar{q}_{t+1}. \tag{27}$$

$A_{0,i}$, $A_{\sigma,i}$, $A_{\tilde{q},i}$ and $A_{\bar{q},i}$ are chosen such that the following equilibrium condition is satisfied (see Appendix A.1):

$$\mathbb{E}_t(r_{i,t+1} + m_{i,t+1}) + \frac{1}{2} Var_t(r_{i,t+1} + m_{i,t+1}) = 0. \tag{28}$$

Note that given $\omega = 1$, the U.S. log wealth-consumption ratio only depends on σ^2_{t+1} and $\bar{q}_{t+1}$. Furthermore, given $r_{i,t+1}$ depends on $z_{i,t+1}$, the country i SDF depends on ω_i. This implies that the weight on the U.S. component affects the pricing mechanism in non-U.S. countries.

Solving the model, country i's model-implied variance risk premium is given as the conditional covariance between the stock return variance and the SDF (Bollerslev et al., 2009, Londono and Zhou, 2017):

$$VP_{i,t} = cov_t(\sigma^2_{r,i,t+1}, m_{i,t+1}), \tag{29}$$

where $\sigma^2_{r,i,t+1}$ is the conditional variance of stock returns, $var_t(r_{i,t+1})$. $VP_{i,t}$ is then given as:

$$VP_{i,t} = \tilde{B}_i \tilde{q}_{i,t} + \bar{B}_i \bar{q}_t, \tag{30}$$

$$\tilde{B}_i = (\theta - 1)\kappa_{1,i}(1 - \omega_i)(A_{\sigma,i}\phi^2_{g,i}\phi^2_{\sigma,i} + \kappa^2_{1,i} A_{\tilde{q},i}(A^2_{\sigma,i}\phi^2_{\sigma,i} + A^2_{\tilde{q},i}\phi^2_{\tilde{q},i})\phi^2_{\tilde{q},i}), \tag{31}$$

$$\bar{B}_i = (\theta - 1)\kappa_{1,i}\omega_i(A_{\sigma,i}\phi^2_{g,i}\phi^2_{\sigma,i} + \kappa^2_{1,i} A_{\bar{q},i}(A^2_{\sigma,i}\phi^2_{\sigma,i}\omega_i + A^2_{\bar{q},i}\phi^2_{\bar{q},i}\omega^2_i)\phi^2_{\bar{q},i}). \tag{32}$$

Given $\theta < 0$ and for any reasonable specification of $\phi_{g,i}$, $\phi_{\sigma,i}$, $\phi_{\tilde{q},i}$, and $\phi_{\bar{q}}$, the model implied non-U.S. VP is increasing in both idiosyncratic and U.S. vol-of-vol where ω_i reguates the sensitivity to U.S. vol-of-vol. For a cross-section of N non-U.S. countries the model-implied VPI, is then given as:

$$
\begin{aligned}
VPI_t &= VP_t - \frac{1}{N}\sum_{i}^{N} VP_{i,t} \\
&= (\bar{B} - \frac{1}{N}\sum_{i}^{N}\bar{B}_i)\bar{q}_t - \frac{1}{N}\sum_{i}^{N}\tilde{B}_i\tilde{q}_{i,t},
\end{aligned} \tag{33}
$$

where $\bar{B}\bar{q}_t$ is the U.S VP. Given that $\frac{1}{N}\sum_{i=1}^{N}\omega_i < 1$, VPI is decreasing in the average idiosyncratic vol-of-vol and increasing in U.S. vol-of-vol. Hence, an increase in VPI is caused by either an increase in U.S. vol-of-vol and/or a decrease in the average idiosyncratic vol-of-vol.

Under no-arbitrage, the one-month ahead expected currency depreciation rate of country i is given by:

$$
\mathbb{E}_t(s_{i,t+1}) - s_{i,t} = \mathbb{E}_t(m_{i,t+1}) - \mathbb{E}_t(m_{t+1}) + \frac{1}{2}Var_t(m_{i,t+1}) - \frac{1}{2}Var_t(m_{t+1}), \tag{34}
$$

which is affine in the state variables $\sigma_{i,t}$, $\tilde{q}_{i,t}$ and $\bar{q}_t$:

$$
\mathbb{E}_t(s_{i,t+1}) - s_{i,t} = c_i + B_{\sigma,i}\sigma_{i,t}^2 - B_{\sigma}\sigma_t^2 + (B_{\bar{q},i} - B_{\bar{q}})\bar{q}_t + B_{\tilde{q},i}\tilde{q}_{i,t}. \tag{35}
$$

The definitions of c_i, $B_{\sigma,i}$, B_{σ}, $B_{\bar{q},i}$, $B_{\bar{q}}$, and, $B_{\tilde{q},i}$ are provided in Appendix A.1. $B_{\sigma,i}$, B_{σ}, $B_{\bar{q},i}$, $B_{\bar{q}}$, and $B_{\tilde{q},i}$ are all negative for any reasonable specification of ϕ_g, $\phi_{g,i}$, $\phi_{\sigma,i}$, and $\phi_{\tilde{q},i}$. The exchange rate of country i is depreciating in country-specific vol-of-vol and appreciating in U.S. vol-of-vol. Similarly, the expected model-implied one-month Dollar factor is defined as the cross-sectional average of exchange rate changes across the N

non-U.S. countries:

$$\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}_t(s_{i,t+1}) - s_{i,t} = \frac{1}{N}\sum_{i=1}^{N} c_i + \frac{1}{N}\sum_{i=1}^{N} B_{\sigma,i}\sigma_{i,t}^2 - B_\sigma\sigma_t^2 \\ + (\frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},i} - B_{\bar{q}})\bar{q}_t + \frac{1}{N}\sum_{i=1}^{N} B_{\tilde{q},i}\tilde{q}_{i,t}. \tag{36}$$

A comparison of Equation (33) and (36) reveals the model-implied link between expected Dollar factor depreciations and VPI. An increase (decrease) in VPI predicts an appreciation (depreciation) of the Dollar factor. An important implication of our model is that, given non-perfect exposure to U.S. vol-of-vol, VPI has more predictive power on the Dollar factor than U.S. VP alone. In the extreme case of with no country-specific vol-of-vol, i.e. $\omega_i = 1$, vol-of-vol, and thereby SDF volatility, are identical across U.S. and non-U.S. countries. In this case, neither individual VPs nor VPI contain any predictive information on currency depreciation rates.

Note that, our model is easily extentable to the case of incomplete markets by introducing non-U.S. investors to derive a convenience yield on U.S. assets. Within our model, the empirical evidence in Section 7 does, however, suggest that an approapiate assumption would be that the convenience yield is linear in VPI and, thereby affine in q_t and $q_{i,t}$. Relaxing the completeness assumption comes, therefore, at the cost of additional complexity that we do not think adds to the analysis.

8.2. Model implied predictability

Next, we illustrate that our model generates predictive power of VPI on the Dollar factor, qualitatively comparable to the empirical evidence in Section 5 and 6. In particular, we show that the model-implied regression coefficient of VPI on future Dollar factor spot changes qualitively match the empirical observed predictability patterns, cf. Figure 2. We also investigate the sensitivity of the model-implied predictability pattern towards changes in the exposure of the global component in vol-of-vol.

The model implied slope coefficient from a regresion of the h-period ahead spot Dollar factor on VPI at time t is given as:

$$\beta_{\bar{x},VPI}(h) = \frac{cov(\frac{1}{N}\sum_{i=1}^{N} s_{i,t+h} - s_{i,t}, VPI_t)}{var(VPI_t)}. \tag{37}$$

Expressions for the covariance and variance in Equation (37) are provided in Appendix A.2. The numerical variance and the covariance and thereby the model-implied regression coefficient depend on the specific parameter values characterizing the growth processes of the U.S. and the non-U.S. countries, in Equation (20)-(24).

For simplicity, we follow Bollerslev et al. (2009) regarding the choice of parameters and focus on the sensitivity of the model-implied regression coefficient to the weight of the global component on vol-of-vol. Appendix A.3 provides the exact values of the parameters.

Figure 5 shows the model-implied regression coefficient provided in Equation (37) for horizons between 1 and 12 months, for three different choices of ω_i: 0.33, 0.66, and 0.99.

Figure 5 about here

The regression coefficient is strictly positive in line with the theoretical hypothesis 1 provided in 3. The model, hence, rationalizes the empirical findings: the Dollar risk premium is increasing in VPI. Furthermore, the model predicts the regression coefficient on the annualized Dollar factor being decreasing in the horizon. This is in line with the empirical evidence in Figure 2b. Last, the coefficients are decreasing in ω_i suggesting that the predictability of VPI is decreasing in the degree of integration between financial markets across countries. Remember, the extreme case of $\omega_i = 1$ corresponds to the case in which all risks are priced identical across countries and leave no currency risk premium. Unless we are situated in this unrealistic case, the VPI should predict the Dollar risk premium. In the other extreme case, $\omega_i = 0$, the model collapses to a simplified version of the model in Londono and Zhou (2017) without global inflation risk. Their model will also reproduce the predictability of VPI. The model presented in the Section is naturally very stylized and can be improved in multiple ways to better mimic empirical observations. The model does, however, provide a simple rationalization for the predictability patterns in Section 5.

9. Conclusion

We provide new empirical evidence that the Dollar factor is predictable by introducing a novel predictor: variance risk premia imbalances (VPI). VPI is defined as the difference between the variance risk premium in the U.S. and the average variance risk premium across non-U.S. countries. VPI explains roughly 10% of next-month Dollar factor variations with t-statistics above 3.5. We argue that VPI proxies the difference in U.S. and non-U.S. SDF volatility which is consistent with our empirical analysis. The predictive power of VPI preserves for bilateral exchange rates and VPI is unrelated to traditional predictors. We show that the predictive power of VPI is economically exploitable to investors and is consistent with demand for U.S. safe assets driving dollar appreciations.

We provide a simple no-arbitrage consumption-based model that rationalize our findings. The model shows that unless SDF volatility is perfectly correlated between the U.S. and non-U.S. countries, VPI has predictive power on the Dollar factor, decreasing in the holding period.

References

Backus, D. K., S. Foresi, and C. Telmer (2001). Affine term structure models and the forward premium anomaly. *Journal of Finance 56*(1), 279–304.

Bakshi, G. and N. Kapadia (2003). Delta-hedged gains and the negtive market volatility risk premium. *Review of Financial Studies 16*(2), 527–566.

Bakshi, G. and D. Madan (2006). A theory of volatility spreads. *Management Science 52*(12), 1945–1956.

Bekaert, G. and M. Hoerova (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics 183*(2), 181–192.

Bollerslev, T., M. Gibson, and H. Zhou (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics 160*(1), 235–245.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *Review of Financial Studies 22*(11), 4463–4492.

Campbell, J. Y. and R. J. Shiller (1988a). The dividend-price ration and expectations of future dividends and discount factors. *Review of Financial Studies 1*(3), 195–228.

Campbell, J. Y. and R. J. Shiller (1988b). Stock prices, earnings, and expected dividends. *Journal of Finance 43*(3), 661–676.

Campbell, J. Y. and S. B. Thompson (2008). Predicting excess stock returns out of sample: Can anything beat the historical average. *Review of Financial Studies 21*(4), 1509–1531.

Carr, P. and L. Wu (2009). Variance risk premiums. *Review of Financial Studies 22*(3), 1311–1341.

Clark, T. E. and K. D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics 138*(1), 291–311.

Colacito, R., S. J. Riddiough, and L. Sarno (2020). Business cycles and currency returns. *Journal of Financial Economics 137*(3), 659–678.

Davies, S. and C. Kent (2020). US dollar funding: An international perspective. *Bank for International Settlements. CGFS Papers 65.*

Della Corte, P., T. Ramadorai, and L. Sarno (2016). Volatility risk premia and exchange rate predictability. *Journal of Financial Economics 120*(1), 21–40.

Du, W., J. Im, and J. Schreger (2018). The U.S. treasury premium. *Journal of International Economics 112*, 167–181.

Engel, C. and K. D. West (2005). Exchange rates and fundamentals. *Journal of Political Economy 113*(3), 485–517.

Epstein, L. G. and S. E. Zin (1989). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica 57*(4), 937–969.

Fan, Z., J. M. Londono, and X. Xiao (2022). Equity tail risk and currency risk premiums. *Journal of Financial Economics 143*(1), 484–503.

Frankel, J. A. and A. K. Rose (1995). Empirical research on nominal exchange rates. *Handbook of international economics 3*, 1689–1729.

Froot, K. A. and K. Rogoff (1995). Perspectives on PPP and long-run real exchange rates. *Handbook of international economics 3*, 1647–1688.

Gourinchas, P.-O., H. Rey, and N. Govillot (2017). Exorbitant privilege and exorbitant duty. *Working paper*.

Goyal, A. and I. Welch (2008). A comprenehsive look at the empirical performance of equity premium prediction. *Review of Financial Studies 21*(4), 1455–1508.

He, Z., A. Krishnamurthy, and K. Milbradt (2019). A model of safe asset determination. *Amercian Economic Review 109*(4), 1230–1262.

Jiang, Z. (2021). US fiscal cycle and the dollar. *Journal of Monetary Economics 124*, 91–106.

Jiang, Z., A. Krishnamurthy, and H. Lustig (2021). Foreign safe asset demand and the dollar exchange rate. *Journal of Finance 76*(3), 1049–1089.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012). The aggregate demand for treasury debt. *Journal of Political Economy 120*(2), 233–267.

Londono, J. M. (2015). The variance risk premium around the world. *Working paper*.

Londono, J. M. and H. Zhou (2017). Variance risk premiums and the forward premium puzzle. *Journal of Financial Economics 124*(1), 415–440.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common risk factors in currency markets. *Review of Financial Studies 24*(11), 3731–3777.

Lustig, H., N. Roussanov, and A. Verdelhan (2014). Countercyclical currency risk premia. *Journal of Financial Economics 111*(1), 527–553.

Maggiori, M. (2017). Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review 107*(10), 3038–3071.

Meese, R. A. and K. Rogoff (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics 14*(1-2), 3–24.

Miranda-Agrippino, S., T. Nenova, and H. Rey (2020). Global footprints of monetary policies. *Working paper*.

Miranda-Agrippino, S. and H. Rey (2020). US monetary policy and the global financial cycle. *Review of Economic Studies 87*(6), 2754–2776.

Newey, W. K. and K. D. West (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies 61*(4), 631–653.

Opie, W. and S. J. Riddiough (2020). Global currency hedging with common risk factors. *Journal of Financial Economics 136*(3), 780–805.

Rapach, D. E., J. K. Strauss, and G. Zhou (2013). International stock return predictability: What is the role of the United States? *Journal of Finance 68*(4), 1633–1662.

Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature 51*(4), 1063–1119.

Verdelhan, A. (2018). The share of systematic variation in bilateral exchange rates. *Journal of Finance 73*(1), 375–418.

Weil, P. (1989). The equity premium puzzle and the risk-free rate puzzle. *Journal of Monetary Economics 24*(3), 401–421.

Table 1: Summary statistics.

This table reports summary statistics of VPI and country-specific variance risk premia along with correlations. Eurozone variance risk premium is constructed as the GDP weighted average of France, Germany, Italy, and Netherlands. VPI and the individual variance risk premia are constructed using data from January 2000 to December 2019 or when available.

	VPI	U.S.	U.K.	Japan	Switzerland	Australia	Canada	Euro
Mean	-0.97	89.21	85.23	111.53	59.71	117.14	108.46	76.22
Median	11.15	98.00	88.00	133.23	77.60	87.83	108.85	107.44
St. dev.	197.10	311.26	280.06	317.51	266.40	189.96	97.29	224.69
Skew.	-2.38	-4.90	-6.04	-2.27	-4.43	1.02	-0.76	-2.21
Kurt.	18.21	46.09	71.56	21.36	37.77	11.14	12.88	11.98
					Correlations			
U.S.			0.82	0.51	0.64	0.43	0.72	0.51
U.K.				0.58	0.81	0.53	0.54	0.51
Japan					0.46	0.68	0.23	0.19
Switzerland						0.48	0.37	0.57
Australia							0.51	0.36
Canada								0.41

Table 2: VPI and the Dollar factor.

This table presents the in-sample predictability results of Equation (13) and (12). The table contains estimates of the coefficients and the degree of explained variation and t-statistics calculated using Newey and West (1994) standard errors with six lags. The regression is carried out using data from January 2000 to December 2019.

	Coefficients	R^2	Coefficients	R^2	Coefficients	R^2
	All		Developed		Emerging	
			Panel A: Excess returns			
Constant	0.12	10.50%	0.05	9.51%	0.15	10.72%
	[0.88]		[0.28]		[1.18]	
VPI	0.66		0.74		0.62	
	[3.79]		[4.09]		[3.55]	
			Panel B: Spot changes			
Constant	-0.05	11.09%	0.04	9.41%	-0.09	11.37%
	[-0.35]		[0.24]		[-0.67]	
VPI	0.67		0.74		0.64	
	[3.89]		[4.07]		[3.67]	

Table 3: The U.S. VP, non-U.S. VP, and the Dollar factor.
This table presents the in-sample predictability results of Equation (13) and (12) in which we split VPI into a U.S. component and a non-U.S. component. The table contains estimates of the coefficients, the degree of explained variation, and the test statistic from performing a Wald test for the coefficient of the U.S. component is equal to minus the coefficient of foreign component. *t*-statistics calculated using Newey and West (1994) standard errors with six lags are shown in brackets, while the *p*-values from the Wald test are shown in parenthesis. The regression is carried out using data from January 2000 to December 2019.

	Coefficients	R^2	Coefficients	R^2	Coefficients	R^2
	All		Developed		Emerging	
			Panel A: Excess returns			
US	0.0033	11.49	0.0037	10.04	0.0031	11.87
	[4.09]		[4.24]		[3.89]	
Non-U.S.	-0.0024		-0.0030		-0.0022	
	[-2.29]		[-2.44]		[-2.23]	
Wald test	2.39		0.89		3.55	
for equality	(0.12)		(0.35)		(0.06)	
			Panel B: Spot changes			
US	0.0034	12.00	0.0037	9.90	0.0032	12.50
	[4.22]		[4.22]		[4.06]	
Non-U.S.	-0.0025		-0.0030		-0.0023	
	[-2.42]		[-2.47]		[-2.34]	
Wald test	2.50		0.89		3.89	
for equality	(0.11)		(0.35)		(0.05)	

Table 4: Longer horizons Dollar factor Predictability.
This table presents the VPI slope coefficients and regression R^2s using excess returns (Panel A) and spot rate changes (Panel B) across the three currency-baskets: All, Developed and Emerging. The t-statistics are calculated using Newey and West (1994) standard errors with lag length equal to the forecast horizon.

Horizon	Coefficients	R^2	Coefficients	R^2	Coefficients	R^2
	All		Developed		Emerging	
			Panel A: Excess returns			
2	0.61	4.19%	0.60	2.99%	0.62	4.88%
	[2.45]		[2.81]		[2.01]	
3	0.61	2.62%	0.53	1.48%	0.66	3.45%
	[1.88]		[1.76]		[1.91]	
6	0.45	0.64%	0.21	0.11%	0.58	1.15%
	[1.45]		[0.52]		[1.27]	
9	0.02	0%	-0.26	0.11%	0.11	0.03%
	[0.05]		[-0.31]		[0.41]	
12	-0.23	0.08%	-0.47	0.27%	-0.13	0.03%
	[-0.28]		[-0.44]		[-0.2]	
			Panel B: Spot changes			
2	0.6	4.19%	0.91	2.99%	0.49	4.88%
	[2.46]		[2.29]		[2.04]	
3	0.59	2.62%	0.89	1.48%	0.47	3.45%
	[1.91]		[2.01]		[1.81]	
6	0.4	0.64%	0.54	0.11%	0.37	1.15%
	[1.72]		[1.18]		[1.02]	
9	-0.05	0%	-0.01	0.11%	-0.05	0.03%
	[-0.13]		[-0.03]		[-0.14]	
12	-0.27	0.08%	-0.3	0.27%	-0.27	0.03%
	[-0.47]		[-0.47]		[-0.47]	

Table 5: Predictability of bilateral exchange rates. Panel regressions.

This table reports results of panel regressions for excess returns and spot rate changes of individual currencies on VPI. The panel regressions include currency fixed effects. For each basket of currencies (Developed, Emerging, and All), we report the slope coefficient on VPI. The *t*-statistics in brackets are computed using robust standard errors clustered by month and currency. The regression is carried out using data from January 2000 to December 2019.

	All		Developed		Emerging	
	Excess returns	Spot rates	Excess returns	Spot rates	Excess returns	Spot rates
VPI	0.71	0.68	0.74	0.74	0.69	0.65
	[3.27]	[3.23]	[3.15]	[3.14]	[3.19]	[3.16]

Table 6: Predictability of bilateral exchange rates.

This table shows the results of estimating VPI on excess returns in the next month of each bilateral exchange rate. We have excluded currencies with less than 36 months of data. The table presents coefficients, the degree of explained variation, and t-statistics calculated using Newey and West (1994) standard errors with six lags. The regression is carried out using data from January 2000 to December 2019. The table continues on the next page.

	Constant	VPI	R^2
Australia	0.22	1.11	9.42%
	[0.87]	[4.07]	
Brazil	0.57	1.02	5.47%
	[1.51]	[2.39]	
Bulgaria	-0.03	0.82	9.11%
	[-0.16]	[4.46]	
Canada	0.06	0.72	7.63%
	[0.36]	[3.62]	
Croatia	0.05	0.86	9.37%
	[0.25]	[4.84]	
Cyprus	0.43	-0.12	0.02%
	[1.59]	[-0.22]	
Czech Republic	0.16	0.94	7.56%
	[0.77]	[3.81]	
Denmark	0.01	0.71	6.26%
	[0.05]	[3.65]	
Egypt	0.99	0.04	0.06%
	[3.67]	[0.63]	
Hungary	0.25	1.21	9.13%
	[1.02]	[4.2]	
Iceland	0.19	0.73	3.22%
	[0.61]	[2.58]	
India	0.19	0.32	2.25%
	[1.49]	[3.29]	
Indonesia	0.07	0.58	5.01%
	[0.28]	[2.03]	
Israel	0.18	0.86	14.77%
	[1.15]	[8.36]	
Japan	-0.18	-0.29	1.16%
	[-0.98]	[-1.41]	
Kuwait	0.04	0.24	12.69%
	[0.97]	[4.08]	
Malaysia	0.07	0.41	4.13%
	[0.44]	[2.43]	
Mexico	0.14	1.02	11.69%
	[0.83]	[5.04]	
New Zealand	0.34	1.17	9.26%
	[1.38]	[4.52]	
Norway	0.05	0.85	6.86%
	[0.23]	[3.11]	
Philippines	0.16	0.18	1%
	[1.2]	[1.52]	
Poland	0.28	1.63	16.47%
	[1.18]	[7.52]	
Russia	0.15	0.95	5.5%
	[0.46]	[3.91]	

	Constant	VPI	R^2
Singapore	0.04	0.38	5.66%
	[0.46]	[1.85]	
Slovakia	1.14	1.25	15.14%
	[3.49]	[4.4]	
South Africa	-0.22	0.55	1.68%
	[-0.68]	[1.49]	
South Korea	0.16	0.92	8.17%
	[0.87]	[4.15]	
Sweden	-0.06	0.92	8.08%
	[-0.25]	[4.02]	
Switzerland	0.08	0.74	6.17%
	[0.53]	[2.83]	
Taiwan	-0.11	0.29	4.4%
	[-1.46]	[2.55]	
Thailand	0.18	0.26	2.17%
	[1.48]	[2.62]	
Ukraine	0.26	1.05	13.3%
	[1.04]	[2.18]	
UK	-0.05	0.78	9.4%
	[-0.3]	[4.61]	
Euro	0.01	0.72	6.4%
	[0.05]	[3.68]	
Average	0.17	0.70	7.02
	[0.72]	[3.32]	

Table 7: VPI and existing predictors.

This table presents the in-sample predictability results of Equation (13) and (12), in which we control for different predictors from the literature: the average currency variance risk premium (XVP), the average forward discount (AFD), and the global financial cycle (GFC). The table contains estimates of the coefficients, the degree of explained variation, and t-statistics calculated using Newey and West (1994) standard errors with six lags are shown in brackets. The regression is carried out using data from January 2000 to December 2019.

	Coefficients	R^2	Coefficients	R^2	Coefficients	R^2
	All		Developed		Emerging	
Panel A: Average currency risk premia						
Constant	0.12	10.58%	0.05	9.51%	0.15	10.91%
	[0.90]		[0.3]		[1.19]	
VPI	0.65		0.74		0.61	
	[3.08]		[3.26]		[2.96]	
XVP	0.06		0.00		0.08	
	[0.90]		[-0.05]		[1.43]	
Panel B: Average forward discount						
Constant	0.12	10.76%	0.03	10.21%	0.15	10.76%
	[0.87]		[0.22]		[1.19]	
VPI	0.65		0.73		0.62	
	[3.07]		[3.24]		[2.94]	
AFD	0.95		1.84		0.32	
	[0.85]		[1.33]		[0.32]	
Panel C: Global financial cycle						
Constant	0.12	11.92%	0.05	11.05%	0.15	11.98%
	[0.85]		[0.28]		[1.11]	
VPI	0.70		0.80		0.66	
	[3.39]		[3.64]		[3.21]	
GFC	-0.22		-0.29		-0.18	
	[-1.27]		[-1.49]		[-1.08]	

Table 8: Out-of-sample predictability.

This table displays the out-of-sample analysis. Panel A presents the results for the Dollar factor, while Panel B presents the results for the bilateral G10 currences. To measure predictability, we consider the R^2_{OoS} of Campbell and Thompson (2008) against the benchmark of a random walk (with drift). The forecasts are constructed using a rolling window of 5 years, implying that the out-of-sample period spans from January 2005 to December 2019. p-values from a Clark and West (2007) test against the benchmark are shown in parenthesis.

	R^2_{OoS} (Random walk)	R^2_{OoS} (Random walk with drift)
	Panel A: The Dollar factor	
Dollar factor	12.51%	10.97%
	(0.03)	(0.02)
	Panel B: Bilateral exchange rates	
Australia	9.22%	10.39%
	(0.02)	(0.05)
Canada	7.34%	8.94%
	(0.03)	(0.03)
Euro	6.36%	7.43%
	(0.02)	(0.03)
Japan	-9.40%	-6.07%
	(0.82)	(0.78)
New Zealand	10.88%	12.21%
	(0.01)	(0.03)
Norway	8.99%	10.73%
	(0.03)	(0.04)
Sweden	9.92%	11.05%
	(0.03)	(0.04)
Switzerland	4.11%	6.02%
	(0.02)	(0.02)
U.K.	12.89%	15.31%
	(0.06)	(0.06)

Table 9: Currency investing strategy.

Panel A presents the results of the VPI strategy. The strategy is long (short) the Dollar factor when VPI is positive (negative). The table shows mean return and Sharpe ratio (SR) for the strategy. The sample spans from February 2000 to December 2019. Panel B presents the same measures as Panel A for the buy-and-hold strategy of the Dollar factor. Panel C presents the abnormal excess returns of the VPI strategy adjustet for the buy-and-hold strategy, the carry trade risk factor (HML) of Lustig et al. (2011) and the excess returns from following the strategy of Lustig et al. (2014) (AFD). t-statistics, calculated using Newey and West (1994) standard errors with six lags, are reported in brackets.

	Panel A: VPI strategy	
	Developed	All
Return	4.10	3.12
	[2.47]	[2.23]
SR	0.50	0.44
	Panel B: Buy-and-hold	
Return	1.14	2.01
	[0.54]	[1.13]
SR	0.14	0.29
	Panel C: Abnormal returns of VPI strategy	
α	3.71	3.05
	[2.17]	[2.03]
β_{DOL}	0.14	0.13
	[0.96]	[1.03]
β_{HML}	-0.04	-0.05
	[-0.57]	[-0.74]
$\beta_{dollar\ carry}$	0.00	0.00
	[0.91]	[0.35]

Table 10: Currency hedging strategies.

This table presents statistical and economic performance measures for global stock portfolios with exposure to the G10 currencies in which currency risk is hedged by different alternatives. The first column contains the results for the VPI-based hedged portfolio, the second column and third columns are for the un-and-fully hedged portfolios, respectively. We report the portfolio average return, standard deviation (STD), Sharpe ratio (SR), Sortino ratio (Sortino), Skewness, Kurtosis, Certainty equivalent (CEV), and performance fee. γ denotes the assumed level of relative risk aversion.

	VPI portfolio	Un-hedged	Full-hedged
Average return	4.78	3.46	2.38
STD	0.15	0.17	0.13
SR	0.31	0.21	0.18
Sortino	0.43	0.28	0.23
Skewness	-0.44	-0.68	-0.81
Kurtosis	3.67	4.64	4.12
CEV	0.01	-0.01	-0.00
Performance fee (γ=5)	-	1.50	2.10

Table 11: VPI and safe asset demand.

This table presents the results from the predictive regressions in Equation (18) and (19) in which we regress demand for U.S. safe assets on VPI. As proxies for U.S. safe assets, we consider CIP violations from 1-year government bonds and 1-year interbank interest rates (Panel A) in addition to net-positions in U.S. Treasury futures from buy-side investors (Panel B). The table contains coeffcients, t-statistics, and R^2s. t-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets

	Constant	VPI	R^2
		Panel A: CIP violations	
Government bonds	16.97	-6.35	17.49%
	[7.96]	[-2.44]	
Interbank rates	15.2	-3.42	4.63%
	[6.75]	[-2.05]	
		Panel B: Buy-side demand	
Net U.S. Treasury futures	0.12	-0.02	2.82%
	[4.02]	[-2.55]	

Figure 1: VPI

This figure plots VPI for our sample spanning from January 2000 to the end of December 2019. The shaded areas mark U.S. recessions, according to NBER.

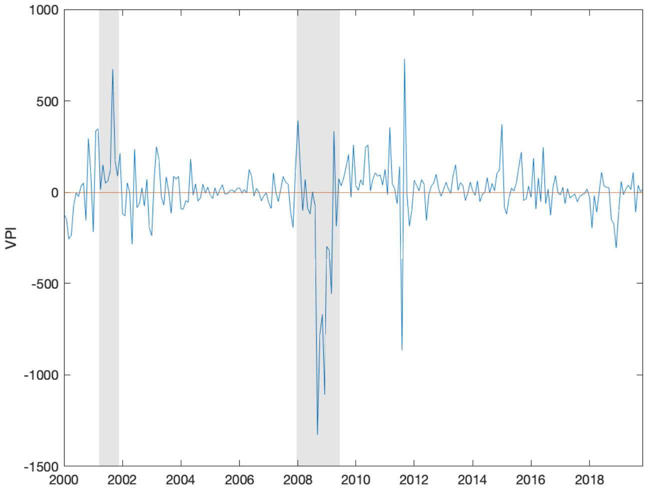
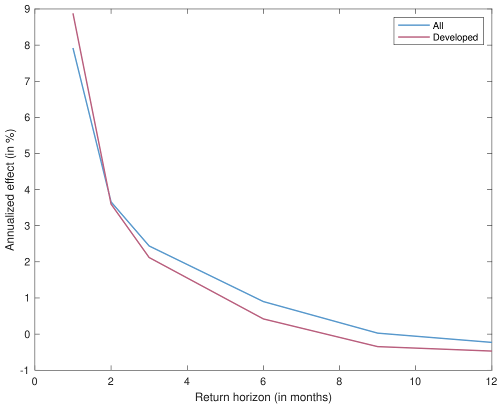
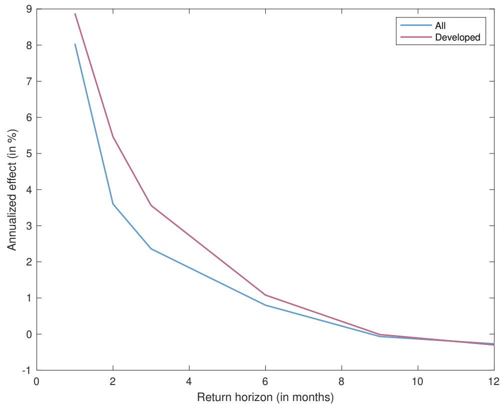


Figure 2: The annuallized coefficient of VPI on the Dollar factor

This figure shows the annualized effect of VPI on the Dollar factor for return horizons between one- and 12-month. The coefficients are estimated using a sample from January 2000 to December 2019 for All (blue line) and Developed (red line).



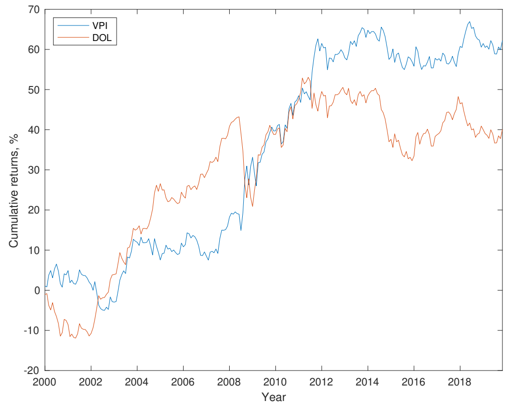
(a) Excess Dollar factor



(b) Spot Dollar factor

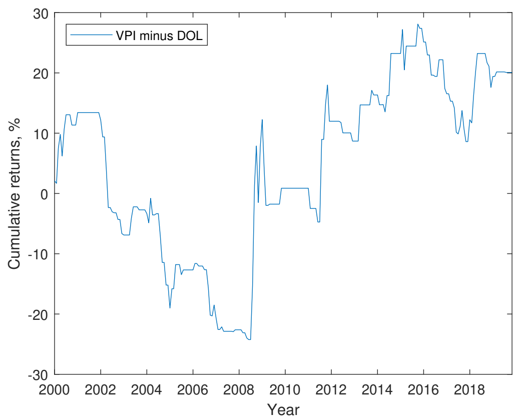
Figure 3: The VPI Dollar strategy: cumulative returns

This figure plots the cumulative returns of the VPI Dollar strategy (blue line) and the Dollar factor (red line). The strategy buys (sells) the Dollar factor when VPI is positive (negative). Panel (a) presents the performance for the All basket and (b) for Developed.

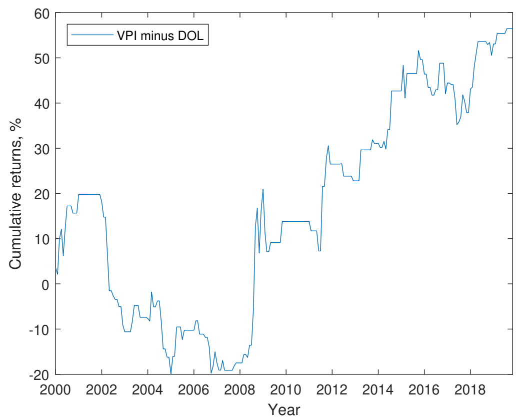


(a) Cumulative returns - All

(b) Cumulative returns - Developed



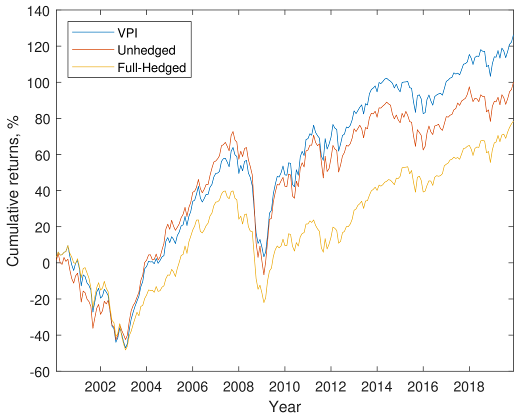
(c) Cumulative return difference - All



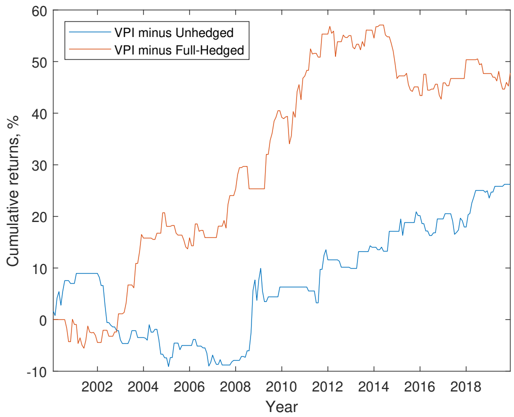
(d) Cumulative return difference - Developed

Figure 4: Hedging: Portfolio performance

This figure plots the cumulative returns of the VPI Dollar strategy (blue line) and the Dollar factor (red line). The strategy buys (sells) the Dollar factor when VPI is positive (negative). Panel (a) presents the performance for the All basket and (b) for Developed.

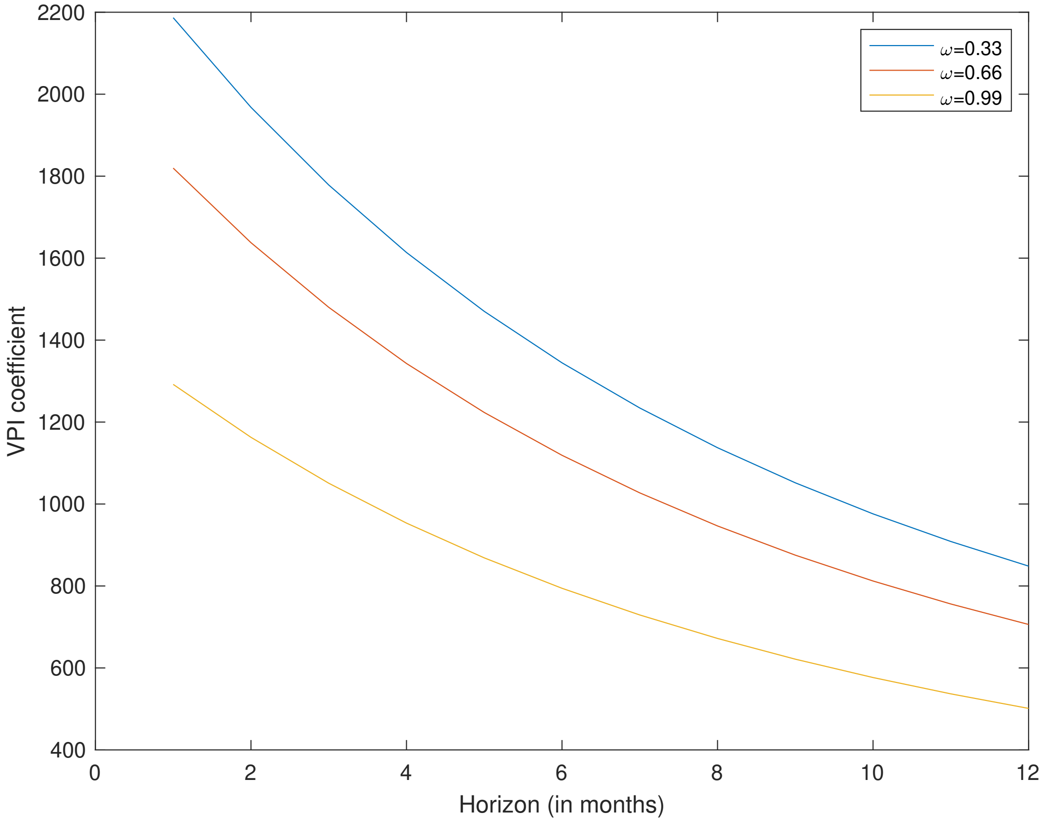


(a) Portfolio returns



(b) Portfolio return differences

Figure 5: Model-implied regression coefficient.
This figure shows the annualized model-implied predictive regression coefficient of VPI on the Dollar factor for return horizons between one- and 12-month. The figure shows the coefficients for three different choices of ω_i which determines the weight on the global component in non-U.S. vol of consumption volatility. The parameters of the model is set similar to the choices in Bollerslev et al. (2009) and Londono and Zhou (2017).



A. Appendix

A.1. Solution to price consumption ratio

Our theoretical model of Section 8 is solved by as standard in the literature using the Campbell and Shiller (1988a) log linerazation of stock returns:

$$r_{i,t+1} = \kappa_0 + \kappa_1 z_{i,t+1} - z_{i,t} + g_{i,t+1} \tag{A.1}$$

and imposing that the log of the wealth consumption ratio is an affine function of the state variables:

$$z_{i,t+1} = A_{0,i} + A_{\sigma,i}\sigma^2_{i,t+1} + A_{\tilde{q},i}\tilde{q}_{i,t+1} + A_{\bar{q},i}\omega_i\bar{q}_{t+1}. \tag{A.2}$$

$A_{0,i}$, $A_{\sigma,i}$, $A_{\tilde{q},i}$, and $A_{\bar{q},i}$ are chosen such that the equilibrium condition:

$$\mathbb{E}_t(r_{i,t+1} + m_{i,t+1}) + \frac{1}{2}Var_t(r_{i,t+1} + m_{i,t+1}) = 0 \tag{A.3}$$

is satisfied.

The two terms of Equation (A.3) are given as:

$$\begin{aligned}
\mathbb{E}_t(r_{t+1} + m_{t+1}) &= \theta \log\delta + \mu(1-\gamma) + \theta(\kappa_{0,i} + A_{0,i}(\kappa_{1,i} - 1) + A_{\sigma,i}(\kappa_{1,i}(\mu_{\sigma,i} + \rho_{\sigma,i}\sigma^2_{i,t}) - \sigma^2_{i,t}) \\
&\quad + A_{\tilde{q},i}(\kappa_{1,i}(\mu_{\tilde{q},i} + \tilde{\rho}_i\tilde{q}_{i,t}) - \tilde{q}_{i,t}) + A_{\bar{q},i}\omega_i(\kappa_{1,i}(\mu_{\bar{q}} + \bar{\rho}\bar{q}_t) - \bar{q}_t)), \qquad \text{(A.4)} \\
Var_t(r_{i,t+1} + m_{i,t+1}) &= \left[\frac{\theta^2}{\psi^2}\phi^2_{g,i} + \theta^2\phi^2_{g,i} - 2\frac{\theta^2}{\psi}\phi^2_{g,i}\right]\sigma^2_{i,t} + \theta^2\kappa^2_{1,i}\left[A^2_{\sigma,i}\omega_i\phi^2_{\sigma,i} + A^2_{\bar{q},i}\omega_i^2\phi^2_{\bar{q}}\right]\bar{q}_t \\
&\quad + \theta^2\kappa^2_{1,i}\left[A^2_{\sigma,i}\phi^2_{\sigma,i} + A^2_{\tilde{q},i}\phi^2_{\tilde{q},i}\right]\tilde{q}_{i,t} \qquad \text{(A.5)}
\end{aligned}$$

The solutions for $A_{0,i}$, $A_{\sigma,i}$, $A_{\tilde{q},i}$, and $A_{\bar{q},i}$ are then given as:

$$A_{0,i} = \frac{\theta \log(\delta) + \mu_i(1-\gamma) + \theta\kappa_{0,i} + \theta\kappa_{1,i}\left(A_{\sigma,i}\mu_{\sigma,i} + A_{\tilde{q},i}\mu_{\tilde{q},i} + A_{\bar{q},i}\omega_i\mu_{\bar{q}}\right)}{\theta(1-\kappa_{1,i})}, \tag{A.6}$$

$$A_{\sigma,i} = \frac{(1-\gamma)^2\phi_{g,i}^2}{2\theta(1-\kappa_{1,i}\rho_{\sigma,i})}, \tag{A.7}$$

$$A_{\bar{q},i} = \frac{(1-\kappa_{1,i}\tilde{\rho}_i) \pm \sqrt{(1-\kappa_{1,i}\tilde{\rho}_i)^2 - \theta^2\kappa_{1,i}^4\phi_{\tilde{q},i}^2\phi_{\sigma,i}^2A_{\sigma,i}^2}}{\theta\phi_{\tilde{q},i}^2\kappa_{1,i}^2}, \tag{A.8}$$

and

$$A_{\bar{q},i} = \frac{(1-\kappa_{1,i}\bar{\rho}) \pm \sqrt{(1-\kappa_{1,i}\bar{\rho})^2 - \theta^2\omega_i\kappa_{1,i}^4\phi_{\bar{q}}^2\phi_{\sigma,i}^2A_{\sigma,i}^2}}{\theta\omega_i\phi_{\bar{q}}^2\kappa_{1,i}^2}. \tag{A.9}$$

The model implied variance risk premium is given as:

$$\begin{aligned}
VP_{i,t} &= cov_t(\sigma_{r,i,t+1}^2, m_{i,t+1}),\\
&= cov(\theta\log(\delta) - \frac{\theta}{\psi}g_{i,t+1} + (\theta-1)r_{i,t+1}, \sigma_{r,i,t+1})\\
&= -\frac{\theta}{\psi}\underbrace{cov_t(g_{i,t+1}, \sigma_{r,i,t+1})}_{=0} + (\theta-1)cov(r_{i,t+1}, \sigma_{r,i,t+1})\\
&= \tilde{B}_i\tilde{q}_{i,t} + \bar{B}_i\bar{q}_t
\end{aligned} \tag{A.10}$$

where

$$\begin{aligned}
\tilde{B}_i &= (\theta-1)\kappa_{1,i}(A_{\sigma,i}\phi_{g,i}^2\phi_{\sigma,i}^2 + \kappa_1^2A_{\tilde{q},i}(A_{\sigma,i}^2\phi_{\sigma,i}^2 + A_{\tilde{q},i}^2\phi_{\tilde{q},i}^2)\phi_{\tilde{q},i}^2),\\
\bar{B}_i &= (\theta-1)\kappa_{1,i}\omega_i(A_{\sigma,i}\phi_{g,i}^2\phi_{\sigma,i}^2 + \kappa_1^2A_{\bar{q},i}(A_{\sigma,i}^2\phi_{\sigma,i}^2\omega_i + A_{\bar{q},i}^2\phi_{\bar{q}}^2\omega_i^2)\phi_{\bar{q}}^2).
\end{aligned}$$

The model-implied expected variation in one-period ahead nominal exchange rates of foreign currency with respect to the dollar is given by:

$$\mathbb{E}_t(s_{i,t+1}) - s_{i,t} = \mathbb{E}_t(m_{i,t+1}) - \mathbb{E}_t(m_{t+1}) + \frac{1}{2}Var_t(m_{i,t+1}) - \frac{1}{2}Var_t(m_{t+1}). \tag{A.11}$$

where

$$\mathbb{E}_t(m_{t+1}) = \theta \log \delta + \mu(1-\gamma) + (\theta-1)(\kappa_0 + A_0(\kappa_1 - 1) + A_\sigma(\kappa_1(\mu_\sigma + \rho_\sigma \sigma_t^2) - \sigma_t^2)$$
$$+ A_{\bar{q}}(\kappa_1(\mu_{\bar{q}} + \bar{\rho}\bar{q}_t) - \bar{q}_t)). \tag{A.12}$$

$$\mathbb{E}_t(m_{i,t+1}) = \theta \log \delta + \mu_i(1-\gamma) + (\theta-1)(\kappa_{0,i} + A_{0,i}(\kappa_{1,i} - 1) + A_{\sigma,i}(\kappa_{1,i}(\mu_{\sigma,i} + \rho_{\sigma,i} \sigma_{i,t}^2) - \sigma_{i,t}^2)$$
$$+ A_{\tilde{q},i}(\kappa_{1,i}(\mu_{\tilde{q},i} + \tilde{\rho}_i \tilde{q}_{i,t}) - \tilde{q}_{i,t}) + A_{\bar{q},i}\omega_i(\kappa_{1,i}(\mu_{\bar{q}} + \bar{\rho}\bar{q}_t) - \bar{q}_t)). \tag{A.13}$$

$$Var_t(m_{t+1}) = = \left[\frac{\theta^2}{\psi^2}\phi_g^2 + (\theta-1)^2\phi_g^2 - 2\frac{\theta}{\psi}(\theta-1)\phi_g^2\right]\sigma_t^2$$
$$+ (\theta-1)^2\kappa_1^2\left[A_\sigma^2\phi_\sigma^2 + A_{\bar{q}}^2\phi_{\bar{q}}^2\right]\bar{q}_t \tag{A.14}$$

$$Var_t(m_{i,t+1}) = \left[\frac{\theta^2}{\psi^2}\phi_{g,i}^2 + (\theta-1)^2\phi_{g,i}^2 - 2\frac{\theta}{\psi}(\theta-1)\phi_{g,i}^2\right]\sigma_{i,t}^2$$
$$+ (\theta-1)^2\kappa_{1,i}^2\left[A_{\sigma,i}^2\omega_i\phi_{\sigma,i}^2 + A_{\bar{q},i}^2\omega_i^2\phi_{\bar{q}}^2\right]\bar{q}_t$$
$$+ (\theta-1)^2\kappa_{1,i}^2\left[A_{\sigma,i}^2\phi_{\sigma,i}^2 + A_{\tilde{q},i}^2\phi_{\tilde{q},i}^2\right]\tilde{q}_{i,t} \tag{A.15}$$

This yields that:

$$\mathbb{E}_t(s_{i,t+1}) - s_{i,t} = c_i + B_{\sigma,i}\sigma_{i,t}^2 - B_\sigma\sigma_t^2 + B_{\bar{q},i}\bar{q}_t - B_{\bar{q}}\bar{q}_t + B_{\tilde{q},i}\tilde{q}_{i,t} \tag{A.16}$$

where

$$
\begin{aligned}
c_i &= (1-\gamma)(\mu_i - \mu) + (\theta-1)\kappa_{0,i} + (\theta-1)A_{0,i}(\kappa_{1,i}-1) + (\theta-1)\kappa_{1,i}(A_{\sigma,i}\mu_{\sigma,i} + A_{\tilde{q},i}\mu_{\tilde{q},i} + A_{\bar{q},i}\omega_i\mu_{\bar{q}}) \\
&- ((\theta-1)\kappa_0 + (\theta-1)A_0(\kappa_1-1) + (\theta-1)\kappa_1(A_\sigma\mu_\sigma + A_{\bar{q}}\mu_{\bar{q}})), \\
B_{\sigma,i} &= (\theta-1)A_{\sigma,i}(\kappa_{1,i}\rho_{\sigma,i}-1) + \frac{1}{2}\left[\frac{\theta^2}{\psi^2} + (\theta-1)^2 - 2\frac{\theta}{\psi}(\theta-1)\right]\phi_{g,i}^2, \\
B_\sigma &= (\theta-1)A_\sigma(\kappa_1\rho_\sigma-1) + \frac{1}{2}\left[\frac{\theta^2}{\psi^2} + (\theta-1)^2 - 2\frac{\theta}{\psi}(\theta-1)\right]\phi_g^2, \\
B_{\bar{q},i} &= (\theta-1)A_{\bar{q}}\omega_i(\kappa_{1,i}\bar{\rho}-1) + \frac{1}{2}\left[(\theta-1)^2\kappa_{1,i}^2(A_{\sigma,i}^2\omega_i\phi_{\sigma,i}^2 + A_{\bar{q},i}^2\omega_i^2\phi_{\bar{q}}^2)\right], \\
B_{\bar{q}} &= (\theta-1)A_{\bar{q}}(\kappa_1\bar{\rho}-1) + \frac{1}{2}\left[(\theta-1)^2\kappa_1^2(A_\sigma^2\phi_\sigma^2 + A_{\bar{q}}^2\phi_{\bar{q}}^2)\right], \\
B_{\tilde{q},i} &= (\theta-1)A_{\tilde{q}}(\kappa_{1,i}\tilde{\rho}_i-1) + \frac{1}{2}\left[(\theta-1)^2\kappa_{1,i}^2(A_{\sigma,i}^2\phi_{\sigma,i}^2 + A_{\tilde{q},i}^2\phi_{\tilde{q},i}^2)\right],
\end{aligned}
\tag{A.17}
$$

A.2. Solution to model implied slope coefficients

Next follows a describtion of how to obtain the components of Equation (37), to show the model implied regression coefficient, of the h-horizon Dollar factor on VPI. As in Londono and Zhou (2017), the model implied h-period ahead spot rate change can be approximated by the compound return based on monthly appreaciation rates:

$$
\begin{aligned}
\frac{1}{h}(s_{i,t+h} - s_{i,t}) \simeq \frac{1}{h}\sum_{j=1}^{h}(s_{t+j} - s_{t+j-1}) \\
&= \frac{1}{h}(c_h + B_{\sigma,i}\sigma_{i,t}^2\frac{(1-\rho_{\sigma,i}^h)}{(1-\rho\sigma,i)} - B_{\sigma,x}\sigma_t^2\frac{(1-\rho_\sigma^h)}{(1-\rho\sigma)} \\
&+ B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})} - B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})} + B_{\tilde{q},x,i}\tilde{q}_{i,t}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)} \\
&+ f(...))
\end{aligned}
\tag{A.18}
$$

where,

$$B_{\sigma,x,i} = (\theta - 1)A_{\sigma,i}(\kappa_{1,i}\rho_{\sigma,i} - 1)$$

$$B_{\sigma,x} = (\theta - 1)A_{\sigma,i}(\kappa_1\rho_\sigma - 1)$$

$$B_{\bar{q},x,i} = (\theta - 1)A_{\bar{q},i}\omega_i(\kappa_{1,i}\bar{\rho} - 1)$$

$$B_{\bar{q},x} = (\theta - 1)A_{\bar{q}}(\kappa_1\bar{\rho} - 1)$$

$$B_{\tilde{q},x,i} = (\theta - 1)A_{\tilde{q},i}(\kappa_{1,i}\tilde{\rho}_i - 1)$$

Then for a set of N currencies we have that the covariance between VPI and the h-period spot Dollar factor, $\overline{\Delta s}_{t+h}$ is given as:

$$cov(VPI_t, \underbrace{\frac{1}{h}\sum_{j=1}^{h}\frac{1}{N}\sum_{i=1}^{N}(s_{i,t+j} - s_{i,t+j-1})}_{\overline{\Delta s}_{t+h}}) = \frac{1}{h}cov(\bar{B}\bar{q}_t - \bar{q}_t\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l - \frac{1}{N}\sum_{l=1}^{N}\tilde{B}_l\tilde{q}_{l,t}$$
$$, \frac{1}{N}\sum_{i=1}^{N}B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})} - B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})} + \frac{1}{N}\sum_{i=1}^{N}B_{\tilde{q},x,i}\tilde{q}_{i,t}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)})$$
$$= \frac{1}{h}cov\left(\bar{B}\bar{q}_t, \frac{1}{N}\sum_{i=1}^{N}B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) + \frac{1}{h}cov\left(\bar{B}\bar{q}_t, -B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right)$$
$$+ \frac{1}{h}cov\left(-\bar{q}_t\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l, \frac{1}{N}\sum_{i=1}^{N}B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) + \frac{1}{h}cov\left(-\bar{q}_t\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l, -B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right)$$
$$+ \frac{1}{h}cov\left(-\frac{1}{N}\sum_{l=1}^{N}\tilde{B}_l\tilde{q}_{l,t}, \frac{1}{N}\sum_{i=1}^{N}B_{\tilde{q},x,i}\tilde{q}_{i,t}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)}\right)$$

where,

$$
\begin{aligned}
&cov\left(\bar{B}\bar{q}_t, \frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) = \bar{B}\frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i}\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}var(\bar{q}_t)\\
&cov\left(\bar{B}\bar{q}_t, -B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) = -\bar{B}B_{\bar{q},x}\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}var(\bar{q}_t)\\
&cov\left(-\bar{q}_t\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l, \frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) = -\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l\frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i}\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}var(\bar{q}_t)\\
&cov\left(-\bar{q}_t\frac{1}{N}\sum_{l=1}^{N}\bar{B}_l, -B_{\bar{q},x}\bar{q}_t\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}\right) = \frac{1}{N}\sum_{l=1}^{N}\bar{B}_l B_{\bar{q},x}\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}var(\bar{q}_t)\\
&cov\left(-\frac{1}{N}\sum_{l=1}^{N}\tilde{B}_l\tilde{q}_{l,t}, \frac{1}{N}\sum_{i=1}^{N} B_{\tilde{q},x,i}\tilde{q}_{i,t}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)}\right) = -\frac{1}{N^2}\sum_{i=l=1}^{N}\tilde{B}_l B_{\tilde{q},x,i}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)}var(\tilde{q}_{i=l,t})
\end{aligned}
$$

Combining all the different covariance terms we obtain:

$$
\begin{aligned}
cov(VPI_t, \overline{\Delta s}_{t+h}) = \frac{1}{h}(var(\bar{q}_t)&\left(\frac{(1-\bar{\rho}^h)}{(1-\bar{\rho})}(\bar{B}(\frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i} - B_{\bar{q},x}) + \frac{1}{N}\sum_{l=1}^{N}\bar{B}_l(B_{\bar{q},x} - \frac{1}{N}\sum_{i=1}^{N} B_{\bar{q},x,i}))\right)\\
&- \frac{1}{N^2}\sum_{i=l=1}^{N}\tilde{B}_l B_{\tilde{q},x,i}\frac{(1-\tilde{\rho}_i^h)}{(1-\tilde{\rho}_i)}var(\tilde{q}_{i=l,t})) \qquad \text{(A.19)}
\end{aligned}
$$

The unconditional first- and second-order moments of the state variables $\bar{q}_t$ and $\tilde{q}_{i,t}$ are given as:

$$
\begin{aligned}
\mathbb{E}(\bar{q}_i) &= \frac{\mu_{\bar{q}}}{1-\bar{\rho}}, \quad \mathbb{E}(\tilde{q}_{i,t}) = \frac{\mu_{\tilde{q},i}}{1-\tilde{\rho}_i}\\
var(\bar{q}_t) &= \frac{\phi_{\bar{q}}^2\mathbb{E}(\bar{q}_t)}{1-\bar{\rho}^2}, \quad var(\tilde{q}_{i,t}) = \frac{\phi_{\tilde{q},i}^2\mathbb{E}(\tilde{q}_{i,t})}{1-\tilde{\rho}_i^2}
\end{aligned}
$$

Then finally, taking the for of the expression for VPI (cf. Equation 33) we get:

$$
var(VPI_t) = \left(\bar{B}^2 + \frac{1}{N^2}\left(\sum_{i=1}^{N}\bar{B}_i\right)^2 - 2\bar{B}\frac{1}{N}\sum_{i=1}^{N}\bar{B}_i\right)var(\bar{q}_t) + \frac{1}{N^2}\sum_{i=1}^{N}\tilde{B}_i^2 var(\tilde{q}_{i,t}). \quad \text{(A.20)}
$$

A.3. Parameter values

This section provides the numerical values for the model parameters. As mentioned, we follow a mix of Bollerslev et al. (2009) and Londono and Zhou (2017) regarding the choice of parameters. Given the parameters are homogenous across U.S. and non-U.S. countries, for simplicity we drop subscripts.

First, we calibrate μ_g and σ_g to empirically match the mean and variance of industrial production growth in the different countries.[16] Next, we set $\rho = 0.979$, $\phi_g = \phi_\sigma = 0.2 < 1$. The persistence parameter of q_t is set to $\rho_q = 0.8$, its mean $\mu_g = 1 \times 10^{-6}(1 - \rho_q)$, and $\phi_q = 0.001$. For the Campbell and Shiller (1988b) constants, we follow Bollerslev et al. (2009) and set $\kappa_1 = 0.9$ while κ_0 is then determined by $\kappa_0 = -\kappa_1 \log(1 - \kappa_1) - (1 - \kappa_1) \log(1 - \kappa_1)$. For the parameters related to the utility function, we set $\delta = 0.997$, $\gamma = 10$, and $\psi = 1.5$.

[16] We obtain the time-series of industrial production growth from OECD.

Table 12: Construction of the variance risk premium imbalance measure: The table presents the Bloomberg tickers for, respectively, the underlying stock indices and the volatility indices used to construct the VPI measure.

Country	Stock index	Stock index ticker	Volatility index ticker
Australia	S&P/ASX 200	AS51	SPA VIX
Canada	S&P/TSX 60	SPTSX60	VIXC
France	CAC40	CAC	VCAC
Germany	DAX	DAX	V1X
Italy	FTSE MIB	FTSEMIB	VIMIB
Japan	Nikkei	NKY	VXJ
Netherlands	AEX	AEX	VAEX
Switzerland	SMI	SMI	V3X
U.K.	FTSE100	UKX	VFTSE
U.S.	S&P 500	SPX	VIX