The U.S. Dollar and Variance Risk Premia Imbalances

Abstract

This paper provides empirical evidence for the difference in variance risk premium in the U.S. against other economies (VPI) having significant predictive power on monthly U.S. Dollar movements. The predictive power of VPI is rationalized by the variance risk premium's economic interpretation and the asset market view of exchange rates. We show that VPI is nonredudant relative to traditional predictors and the predictive evidence has significant economic value for investors.

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

JEL Classification: G12, G15, F31, F37

1. Introduction

The U.S. Dollar (USD) has a dominant position in the international financial markets and is the most important driver of exchange rates (Lustig et al., 2011, Verdelhan, 2018). Yet, the literature has put little attention on the predictability of the USD. To measure USD movements, we consider the Dollar factor defined as the returns to a long position in a currency basket and a short position in the USD. This paper introduces a new strong predictor of the Dollar factor, variance risk premia imbalances (VPI). We define VPI as the difference between the variance risk premium in the U.S. and the average variance risk premium across nine developed economies. In line with financial theory, VPI is a powerful predictor of monthly spot rate changes and excess returns to the Dollar factor. The gains in predictability are economically exploitable to investors - both for investing and currency hedging.

Exchange rate movements are traditionally closely related to a random walk, suggesting no evidence of predictability (Meese and Rogoff, 1983, Engel and West, 2005, Della Corte and Tsiakas, 2012, Ahmed et al., 2016). That said, several studies find a strong common factor structure in the cross-section of currencies (Lustig et al., 2011, Verdelhan, 2018, Korsaye et al., 2020). Figure 1 presents the degree of explained variation of the first 5 PCA factors for our cross-section of currencies.

Figure 1 about here

For developed countries[1], the first PCA factor explains 65% of the total variation in the cross-section. For all countries, it is 55%. With a correlation of 99%, the first PCA factor is strongly related to the Dollar factor, which implies that predictability of the Dollar factor translates directly into predictability of bilateral exchange rates. In particular, among developed countries.

A no-arbitrage condition (the asset market view of exchange rates) implies that exchange rates are given as the ratio between the foreign and domestic discount factors.

[1]Defined as Australia, Canada, Denmark, Japan, New Zealand, Norway, Switzerland, Sweden, UK, and the Euro

The definition implies that short-term log exchange rate movements consist of two components: the difference in interest rates and the difference in SDF volatility. While existing literature focuses on predictors related to the average interest rate difference, e.g., Lustig et al. (2014), we argue that VPI is related to the difference in SDF volatility given that variance risk premium measures the compensation required by investors for taking variance risk. For instance, several studies show a link between risk aversion and variance risk premium (Bakshi and Kapadia, 2003, Bakshi and Madan, 2006, Bollerslev et al., 2011), while others show a link between volatility of consumption volatility and variance risk premium (Bollerslev et al., 2009, Londono, 2015, Londono and Zhou, 2017). Both economic interpretations of the variance risk premium suggest a link to the volatility of the stochastic discount factor. Combining the economic interpretations of the variance risk premium and the no-arbitrage condition for exchange rate predicts VPI to have predictive power for the Dollar factor both measured in spot-rates and excess returns.

To test the motivational hypotheses empirically, we consider three standard currency baskets; developed, emerging, and all. VPI is highly significant as a predictor for the Dollar factor, both economically and statistically, with R^2s ranging from 9.41% to 11.37% for excess returns. A one-standard-deviation increase in VPI predicts a Dollar factor increase of up to 0.74 percentage points depending on the currency basket. The results are almost identical for spot rate changes, confirming that VPI is related to the average difference in SDF volatilities and not interest rates. The common factor structure in currencies suggests that predictability of the Dollar factor should translate into predictability of bilateral exchange rates. The VPI coefficient has the predicted sign for 32 and is highly significant for 28 of the 34 currencies in our cross-section. The average R^2 is 7.02%, which confirms the predictive power of VPI for bilateral exchange rates.

Our findings remain unchanged when we control for both the average forward discount and currency risk premium, considered in Lustig et al. (2014) and Londono and Zhou (2017), respectively. This suggest that VPI is non-redundant to traditional predictors. Londono and Zhou (2017) furthermore, document, that the U.S. variance risk premium itself is related to bilateral exchange rates. Decomposing VPI into two terms: a U.S. and an "other" component, we find that both components are significant with opposite signs. The findings are consistent with Londono and Zhou (2017) but also suggest that only including the U.S. component results in a misspecified model.

In-sample predictability does not necessarily translate into out-of-sample predictability, as noted by Rossi (2013). However, the predictive power of VPI on the Dollar factor is preserved out-of-sample, with an R^2 (cf. Campbell and Thompson (2008)) of 10.97% (12.51%) relative to a random walk (with drift). The out-of-sample predictability for the Dollar factor carries over to predicting individual currencies as well. Considering the G10 currencies, we find, in line with the in-sample evidence, that VPI superiorly forecasts future currency excess returns for all G10 currencies except the Japanese yen relative to a random walk (with drift) with out-of-sample R^2s between 4.11% (6.02%) and 12.89% (15.31%).

We provide three different ways for an investor to utilize the newly discovered evidence of currency predictability. First, inspired by Lustig et al. (2014), we construct a Dollar timing strategy conditional on the sign of VPI: the timing strategy is long (short) in the Dollar factor, and short (long) the USD, whenever VPI is positive (negative). This strategy delivers significant excess returns and Sharpe ratios. Second, we sort all the individual currencies into portfolios based on their excess return forecast. With monthly rebalancing, a long-short strategy delivers significant positive excess returns and Sharpe ratios of similar magnitude to equities. Finally, we show that an international investor obtains sizeable economic gains by using VPI to optimize the hedge position in currency forward contracts.

VPI is largely uncorrelated with traditional factors related to global economic risk and conditions which cannot explain our findings. In particular we consider; the global risk factor of Miranda-Agrippino et al. (2020), FX volatility innovations as in Menkhoff et al. (2012), the global economic policy uncertainty index of Baker et al. (2016), the U.S. industrial production growth, and the difference in output gap between the U.S. and the rest of the world (Colacito et al., 2020). Overall, VPI remains a new strong predictor of the Dollar factor.

1.1. Related literature

Our work is closely related to a long list of literature on the predictability of exchange rates. 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 (Engel and West, 2005) out-of-sample. Rossi (2013) finds that exchange rate movements are well described by a random walk. Engel and West (2005) find that exchange rate movements are disconnected from economic fundamentals in the short horizon. de Los Rios (2009) focuses on affine term structure models and finds that none of the models reliably outperforms a random walk out-of-sample across all currency pairs. Ahmed et al. (2016) find that it is difficult to outperform a random walk out-of-sample. Another research area relates to common factors in the cross-section of currencies. Lustig et al. (2011) identify two common factors: the Dollar factor and the HML factor (confirmed by Verdelhan (2018) and Korsaye et al. (2020)). While several studies have examined the predictability of the HML factor (Menkhoff et al., 2012, Bakshi and Panayotov, 2013), the focus on the most important factor, the Dollar factor (Verdelhan, 2018), has been more limited. One exception is Lustig et al. (2014), who examine the predictive ability of the average forward discount for developed countries on the Dollar factor. They find that the average forward discount is significant at longer horizon returns but not at shorter. We contribute by showing that VPI is a strong predictor of short-term excess returns and spot changes on the Dollar factor while the predictive power decreases at longer horizon returns.

We are not the first to examine the information in options about future returns. We focus, more specifically, on the variance risk premium, i.e., the difference between implied and realized variance. The variance risk premium has several economic interpretations. For instance, Bollerslev et al. (2011) shows that, in a Heston model, the variance risk premium is proportionale to the relative risk aversion while Bollerslev et al. (2009) show that in a consumption based model variance risk premium is related to the volatility of consumption volatility. Both interpretations suggest that the variance risk premium is related to SDF volatility. The variance risk premium is a known return predictor in the literature. Focusing on stock return predictability, Bollerslev et al. (2009) find that the U.S. variance risk premium is a strong predictor of U.S. market returns, while Bollerslev et al. (2014) confirm the findings in an international context. Focusing on currencies, Della Corte et al. (2016) find that the individual volatility risk premium is significant in cross-sectional predictability. Londono and Zhou (2017) find that a global average of currency variance risk premia significantly predicts bilateral exchange rates in-sample. Londono and Zhou (2017) furthermore, show, that the U.S. variance risk premium is significant. The focus in the existing literature is on either currency options or the U.S variance risk premium. We contribute to the literature by showing both in- and out-of-sample that accounting for foreign country variance risk premia is highly significant for predicting the Dollar factor.

The remainder of the paper is organized as follows. Section 2 provides a theoretical motivation for the difference in variance risk premiums being relevant for forecasting the Dollar factor. Section 3 describes the data and how to construct our variance risk premium imbalance (VPI) measure. Section 4 provides in-sample evidence that VPI is highly significant for predicting the Dollar factor and, implied by the common factor structure of Lustig et al. (2011), also bilateral exchange rates. Section 5 shows that the predictive ability is preserved in an out-of-sample analysis for both the Dollar factor and bilateral currencies. In Section 6, we examine whether the gain in predictability provides value for an investor in a simple dynamic currency hedging exercise. Section 7 presents some robustness of our measure relative to existing measures related to global risk and macroeconomic conditions. Section 8 concludes.

2. 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 purely empirical, VPI has a theoretical foundation in the asset market view of exchange rates.

2.1. 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 other countries:

$$
\begin{aligned}
VPI_t &= VP_{US,t} - \overline{VP}_t \qquad (1)\\
\overline{VP}_t &= \frac{1}{N}\sum_i^N VP_{i,t}\ \forall i \neq US,
\end{aligned}
$$

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

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

$\mathbb{Q}$ ($\mathbb{P}$) denotes the risk-neutral (physical) measure, and $\sigma_{i,t,t+1}$ is the country i, stock market return volatility over the period from t to $t+1$. To estimate the $\mathbb{Q}$ 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) can be viewed as the expected cost of entering a long position in a variance swap. VP, hence, 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). Following this intuition, VPI captures the average difference in required variance risk compensation and an increase in VPI implies an increase in the price of hedging variance risk in the U.S. relative to other countries. Several studies suggest that the 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 the VP may be a proxy for the level of relative risk aversion, while Bollerslev et al. (2009) show that the VP is a risk premium for volatility of consumption-volatility.

2.2. Theoretical motivation

Our starting point to motivate the predictive ability of VPI on the Dollar factor is the asset market view of exchange rates, i.e., under no-arbitrage, each exchange rate (relative to USD) is determined by the ratio between the foreign and U.S. stochastic discount factors (SDFs):

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

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

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

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 (market-price of risk), W_t is a Brownian motion, and $S(t)$ is the exchange rate measured as domestic currency prices per unit of foreign currency.

Applying Itô's lemma to the expression for the log exchange rate reveals:

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

The Dollar factor is given as a cross-sectional average of changes across currencies, meaning that the instantaneous dynamics of the Dollar factor is

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

$\bar{r}$ and $\bar{\lambda}$ denote a cross-sectional average of, the foreign short interest rate and the SDF volatility, respectively.

An Euler-discretization of Equation (7) suggests that expected short-term movements in the Dollar factor can be decomposed into two terms: the average difference in interest rates and the average difference in the SDF volatility. Given the economic interpretation of VP, 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. stock index and the rest of the world have equal positive exposure to the risk factor. If U.S. investors require higher compensation for the risk factor exposure relative to investors in the rest of the world, investors can earn an arbitrage unless the exchange rate reflects the difference in risk compensation.[2] In this case, Equation (3) predicts the USD 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 two hypotheses: VPI has predictive power of the Dollar factor with (1) a positive coefficient and (2) for both excess returns and spot rate changes.

3. Data

3.1. VPI

To construct VPI, we consider the headline stock index of the following countries; Australia, Canada, France, Germany, Italy, Japan, Netherlands, Switzerland, United Kingdom, and United States. We construct a Euro VP as the GDP weighted average of the VPs available for the Eurozone countries.[3] Daily index prices and option-implied volatility indices are sourced from Bloomberg, and we construct our measure using end-of-month observations following Equation (1). Table 1 provides an overview of the applied stock and corresponding implied volatility indices.

Table 2 reports summary statistics of VPI along with summary statistics and correlations for the country-specific VPs.

Table 1 and Table 2 about here

Both the mean and median VP is 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

[2] 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.

[3] Our predictive results are qualitatively and quantitatively the same if we had replaced the Euro VP measure with VP on the Euroxx50 index.

VP deviates substantially from the normal distribution, with a rather high kurtosis and negative skewness (except Australia). 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). 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 2 plots VPI.

FIGURE 2 ABOUT HERE

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.

3.2. Currency data

We consider the daily spot and forward exchange rates spanning from January 2000 to the end of December 2019 measured in USD per unit of foreign currency obtained from Thomson Reuters. Given the dataset, we construct monthly (end-of-month) log spot changes and excess returns given 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 our cross-section into three currency baskets: Developed, Emerging, and All. Developed is defined in italic above, Emerging is the rest, and All is all.

In accordance with Lustig et al. (2014), we exclude USD-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 USD - both in terms of excess returns (excess Dollar factor, $\overline{rx}_{t,j}$) and spot rate changes (spot Dollar factor, $\overline{s}_{t,j}$). More specifically, the two are defined as

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

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

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 USD. 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.

4. Currency predictability and VPI

This section investigates whether the theoretical prediction holds empirically. First, we show that VPI is a strong predictor of the Dollar factor for three different baskets of currencies: all, developed, and emerging. Next, motivated by the common factor structure of Lustig et al. (2011), we examine whether the gain in predictability carries over to predictability of individual bilateral exchange rates. Last, we compare VPI with existing known currency predictors from the literature (Lustig et al., 2014, Londono and Zhou, 2017).

4.1. 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 predictive regressions of VPI on the Dollar factor, $\overline{\Delta s}_{t+1,j}$ and $\overline{rx}_{t+1,j}$:

$$\overline{\Delta s}_{t+1,j} = a + \psi VPI_t + \eta_{t+1}, \tag{12}$$

$$\overline{rx}_{t+1,j} = a + \zeta VPI_t + \varepsilon_{t+1}, \tag{13}$$

For ease of interpretation, we standardize VPI. Table 3 presents the estimated ψ- and ζ coefficients for the different currency baskets along with t-statistics (in brackets) calculated by the procedure of Hansen and Hodrick (1980).

Table 3 about here

Focusing on the excess Dollar factor, the VPI coefficients are significant (both economic and statistical) for all currency baskets with t-statistics ranging form 2.96 and 3.27. [4] Considering the Developed basket, a one standard deviation increase in VPI predicts an increase in the excess Dollar factor of 0.74 percentage points over the following month. The coefficients are slightly smaller for the other baskets: 0.62 and 0.63 for Emerging and All, respectively. The implication of this is; an increase (decrease) in the U.S. VP relative to an average of foreign VPs, predicts an increase in the average excess returns of the currency basket relative to the USD. All coefficient estimates are statistically significant at the 1% level. The regressions deliver substantial degrees of explained variations, ranging from 9.71% to 10.72%. The coefficients for the spot Dollar factor are similar both in

[4] The t-statistics are slightly higher applying Newey-West standard errors.

magnitude and t-statistics; all significant at the 1% level, and R^2s ranging from 9.11% to 11.61%. The almost identical results for the excess and spot Dollar factor confirms that VPI is related to the difference in SDF volatility.

4.2. VPI and bilateral exchange rates

Next, we examine whether predictability for the Dollar factor spills-over to predictability for individual currencies. Given the 99% correlation between the first PCA factor and the Dollar factor, we should expect that predictability of the Dollar factor translates into predictability of bilateral exchange rates. We examine this hypothesis by, first, running a panel regression of the bilateral exchange rates on VPI and, secondly, individual regressions for each currency. The panel regressions are given as:

$$\Delta s_{t+1}^{i} = \delta_i + \zeta VPI_t + \hat{\varepsilon}_{t+1}, \tag{14}$$

$$rx_{t+1}^{i} = \alpha_i + \psi VPI_t + \varepsilon_{t+1}, \tag{15}$$

where α_i and δ_i are currency-fixed effects such that only the slope coefficients of VPI are constrained to be equal across currencies. Table 4 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 4 about here

Overall, the coefficients of VPI are almost identical to the results for the Dollar factor (cf. Table 3), ranging from 0.69 to 0.74 for excess returns and 0.65 to 0.74 for spot rates changes, all statistically significant at the 1% level.

To explore the heterogeneity in the predictive power of VPI, we also run individual regressions for each currency. Table 5 reports the output from regressing each excess currency return on VPI individually.

Table 5 about here

The coefficient on VPI is significant at the 1% (5%) level for 24 (28) of the 34 currencies in our sample. The mean slope coefficient of the standardized VPI is 0.70, the mean t-statistic is 3.32, and the mean R^2 is 7.02%. Unlike all other currencies, the VPI coefficient for JPY is negative but insignificant. A possible explanation might be the currency's characteristic as a safe-haven currency (Ranaldo and Söderlind, 2010).

4.3. VPI and existing predictors

The following section explores the relation between VPI and existing predictors. In particular, we consider the U.S. VP, currency variance risk premium (XVP) as defined in Londono and Zhou (2017) (LZ), and the average forward discount (AFD) documented by Lustig et al. (2014) (LRV).

4.3.1. VPI and the U.S. VP

LZ document that the U.S. VP by itself is a significant predictor for spot rate changes. A natural question is whether the U.S. VP drives the predictive power of VPI. To examine this, we regress the excess returns and spot rate changes on the two components of VPI in Equation (1):

$$\overline{\Delta s}_{t+1} = b + \zeta VP_{US,t} + \tilde{\zeta}\overline{VP}_t + \hat{\epsilon}_{t+1}, \tag{16}$$

$$\overline{rx}_{t+1} = a + \psi VP_{US,t} + \tilde{\psi}\overline{VP}_t + \epsilon_{t+1}. \tag{17}$$

If the U.S. VP drives the predictive power of VPI on the excess Dollar factor (spot Dollar factor), then $\tilde{\psi}$ ($\tilde{\zeta}$) would be statistically insignificant. Furthermore, if the two components are equally important, the sum of ψ and $\tilde{\psi}$ (ζ and $\tilde{\zeta}$) would not be significantly different from zero.

Table 6 presents the regressional results.

Table 6 about here

In line with LZ, we find that the U.S. VP significantly predicts both the excess Dollar factor and the spot Dollar factor for all currency baskets. However, the coefficient for $\overline{VP}_{t,t+1}$ is also statistically significant (at the 5% level), with negative coefficients, for both excess returns and spot rate changes. Regarding whether the effect of $VP_{US,t}$ and $\overline{VP}_t$ is equal in absolute terms, we cannot reject the hypothesis for the baskets; All and Developed. For Emerging, the Wald test delivers a p-value of, respectively, 0.05 and 0.06 and are hence, borderline significant. Note that $\overline{VP}_t$ is defined for developed countries implying that the measure does not contain any information from emerging economies. So even though $\overline{VP}_t$ is significant, it is less surprising that the effect of the two components is unequal. In sum, the driver of the Dollar factor is the U.S. VP relative to the foreign VP, not just the level of the U.S. VP.

4.3.2. VPI and currency variance risk premia

Prior studies have examined the predictive power of variance risk premia on currencies themselves. LZ find, in-sample, that a global average of currency variance risk premia (XVP) significantly predicts bilateral exchange rates, while Della Corte et al. (2016) find that the individual volatility risk premium, defined as the difference in square-root variance under $\mathbb{Q}$ and $\mathbb{P}$, contains cross-sectional predictability.

To examine the connection between VPI and XVP, we follow the approach of LZ and 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, GBP, JPY, AUD, CAD, CHF. In accordance with LZ, we construct XVP by taking an equal-weighted average across the six variance risk premia.

The correlation between the two time series is just 0.08, suggesting that the two time series contain different information. We expand the models of Equation (13) and (12) with the XVP. The estimated coefficient values are presented in Table 7.

Table 7 about here

Controlling for XVP in Equation (13) and (12), the coefficients of VPI are completely unaffected - both in terms of t-statistics and the size of the coefficients. The coefficients of the XVP variable are insignificant, and the degree of explained variation is unaffected across all currency baskets. Overall, our results remain strong when controlling for the XVP and the variable does not provide an explanation for the findings.

4.3.3. VPI and the average forward discount

LRV find that the average forward discount (AFD), which for a cross section of N_j currencies within a basket j is defined as:

$$AFD_{t,j} = \frac{1}{N_j} \sum_{i=1}^{N_j} f_{t,t+1,i} - s_{i,t}, \tag{18}$$

has substantial predictive power of currency depreciation rates. Under the covered interest parity, AFD captures the average interest rate difference and, thus, is related to the first term in Equation (7). The correlation coefficient between VPI and AFD is just -0.04 which confirms that VPI is unrelated to the average interest rate difference. Table 8 presents the coefficients for VPI and AFD.

TABLE 8 ABOUT HERE

The coefficients of VPI and R^2s are unaffected, and the coefficients of the AFD variable are all insignificant. Hence, the documented predictability by VPI is, not driven by the AFD.

5. Out-of-sample evidence

The section provides evidence that the in-sample predictability translates into out-of-sample - both in terms of the Dollar factor and bilateral exchange rates. We will focus on excess returns since the results are similar to those of spot rate changes. In this section, we utilize the findings in two ways: first, inspired by Lustig et al. (2014), we construct a simple Dollar timing strategy based on the sign of VPI. Next, we consider a portfolio sort in which currency portfolios are constructed based on the bilateral excess return forecasts. As we take the perspective of an investor seeking to utilize the predictability, we apply discrete returns instead of log returns.[5]

[5] We find qualitatively similar results using log returns.

5.1. 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.[6] For this exercise, the Dollar factor denotes the average excess returns of the currency basket containing developed currencies. Panel A in Table 9 reports out-of-sample R^2s, cf. Campbell and Thompson (2008) and Goyal and Welch (2008). A positive R^2 indicates that the predictive regression has a lower mean squared prediction error than the random walk or the random walk with drift (historical average). 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 9 about here

Our model delivers sizeable out-of-sample R^2 of 10.97% (12.51%) against a random walk (with drift) significantly above zero at the 5% level. In sum, we find that the in-sample evidence translates into out-of-sample predictability.

5.2. A Dollar timing strategy

Motivated by the out-of-sample results, we construct a simple investment strategy that exploits the predictability of the Dollar factor by VPI: the VPI Dollar strategy. The timing simply buys the Dollar when VPI is positive and sells otherwise.

Figure 3 shows the cumulative returns of the simple timing strategy. Panel (a) presents the performance for Developed and Panel (b) for All. As the results are very similar, we comment on Panel (b). At the end of our sample, the VPI Dollar strategy has a cumulative return of 80%.[7] The returns are mainly generated during the period from the end of 2007 to the end of 2011, over which the cumulative return increases sixfold. The strategy is long

[6] We find qualitatively similar results using an expanding window.

[7] 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.

in the Dollar factor 59% of the months but is mainly short during the years of the global financial crisis (cf. Figure 2), during which the USD had long periods of appreciation. For instance, from May 2008 to March 2009, the Dollar factor for developed had an average monthly excess return of -1.66%. The strategy has a pickup during early 2018 in which VPI signals a short position in the Dollar factor. For comparison, Figure 3 also plots the cumulative returns of the Dollar factor. This has a similar trajectory as the VPI Dollar strategy but lower, overall, testifying to the value of VPI as a predictor of the Dollar factor.

FIGURE 3 AND TABLE 9 ABOUT HERE

Table 9 reports the average returns and Sharpe ratios (measured in U.S. dollars) of the VPI Dollar strategy. For the average returns, we show t-statistics based on Newey-West standard errors in brackets. The annualized average returns are 4.10% (Developed) and 3.12% (All) and Sharpe ratios of 0.50 (Developed) and 0.44 (All). A constant long position in the Dollar factor would generate mean returns of 1.14% (Developed) and 2.01% (All) and Sharpe ratios of 0.14 (Developed) and 0.29 (All), showing sizeable performance gains of timing.

5.3. Bilateral out-of-sample prediction

Next, we exploit the predictability of the Dollar factor by VPI for out-sample-of predictions of bilateral currency excess returns. Let, $\hat{\overline{rx}}_{t+1}$, denote the forecasted Dollar factor (cf. Section 5.1), then the currency specific excess return is forecasted via:

$$rx^i_{t+1} = c + \zeta \hat{\overline{rx}}_{t+1} + \varepsilon_{t+1}. \tag{19}$$

The constant in Equation (19) acknowledges the evidence of additional common currency factors than the Dollar factor. For instance, Lustig et al. (2011) find that the return of a currency carry strategy explains a significant fraction of cross-sectional variation in currencies while Colacito et al. (2020) suggest the existence of a business cycle factor.

Including a constant allows for a systematic pricing error from a one-factor model in which the Dollar factor is the only risk factor.

In the interest of space, we focus on the cross-section of G10 currencies: AUD, CAD, CHF, EUR, GBP, JPY, NZD, NOK, and SEK. R^2s are reported in Table 10 with p-values in parenthesis.[8] Panel A and B contain the results using a random walk and random walk with drift, respectively, as a benchmark. Since the results are very similar, we focus on the results in Panel A.

Table 10 about here

Consistent with our in-sample evidence, the out-of-sample R^2 is highly positive for all currencies except JPY, ranging from 4.11% (CHF) to 12.89% (GBP), using a random walk as the benchmark. For AUD, CAD, NOK, NZD, SEK, CHF, and EUR, the out-of-sample R^2s are significantly above zero, at the 5% level, and the 10% level for the other currencies (disregarding JPY). The negative R^2 for the JPY fits well with our in-sample results, confirming that for this currency, there is no return-predictability by VPI. In sum, these results testify to the predictive power of VPI even out-of-sample.

5.4. Portfolio sort on out-of-sample forecasts

Next, we analyze whether the bilateral forecasts can be utilized for investing using a portfolio sort. At the end of each month t, we sort the currencies into five portfolios based on the out-of-sample forecast, cf. Section 5.3. The currencies are ranked from lowest to highest; portfolio 1 (P1) contains the lowest forecasted excess returns, and portfolio 5 (P5) the highest. In addition, we construct a long-short portfolio with long position P5 and short P1. We apply two different portfolio sorts. One uses the All basket, and the other uses the Developed. For the sort on All (Developed), the Dollar factor, $\hat{\overline{rx}}_{t+1}$, is defined using the All (Developed) basket.[9]

[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_{OS} is 7.10% for the entire cross-section when considering the random walk as the benchmark.

[9] Consistent with evidence of the Carry factor being more profitable when including all countries relative to just developed, including a constant in Equation (19) has an impact on the results for the all countries currency basket. For the developed basket, the portfolio sort is more profitable applying a one-factor model without intercept.

Table 11 presents annualized mean returns with t-statistics (Newey-West standard errors) in parenthesis and Sharpe ratios.

Table 11 about here

For both portfolio sorts, the average returns are monotonically increasing from P1 to P5. P1 has an average return of -0.91% when sorting on the All basket (Panel A) and -2.62% for Developed (Panel B). For P5 the average returns are 3.22% (All) and 2.12% (Developed) with Sharpe ratios of 0.36 (All) and 0.20 (Developed). The last column reports the returns of the long-short portfolio. The strategy has averaged returns of 4.13% (All) and 4.74% (Developed), both statistically significant at the 5% level. The Sharpe ratios for the long-short strategy are 0.54 and 0.47, for All and Developed, respectively. The results document that an investor who forecasts currency returns via VPI can generate attractive zero-cost returns with Sharpe ratios comparable to stocks.

6. A dynamic currency hedging exercise

In the spirit of the previous section, we continue to explore the economic gains of the Dollar factor predictability by the VPI. We consider the usage in currency exposure arising from international investments. Concretely, we explore the economic gains for an investor holding a portfolio of foreign stocks. The portfolio incurs a foreign exchange rate exposure which she can hedge using forward contracts. The optimal hedge position in forwards is estimated using VPI. The structure of the exercise is similar to Opie and Riddiough (2020).

6.1. Setup

We consider a mean-variance investor who holds positions in international stocks denominated in foreign currency. She can hedge the currency risk using the FX forward market. That is, she chooses a portfolio p consisting of international stocks and currency forward contracts to maximize her utility function given as:

$$\max_{w_t} U(w_t) = \mathbb{E}_t \left(r_{p,t+1} - \frac{\gamma}{2} Var(r_{p,t+1}) \right), \tag{20}$$

where $r_{p,t+1} = w_t' r_{t+1}$ with r_t being a vector of asset returns, w_t weights, and γ denotes the level of risk-aversion. Given our objective of currency hedging, we follow Opie and Riddiough (2020) and assume that the investor holds an equal-weighted portfolio of international stocks. This implies that the optimization problem for the investors reduces to choosing the weights for the forward contracts, $w_{f,t}$. We restrict the weights in the forward contract to the interval $w_{f,t} \in [-w_{x,t}, 0]$ where $w_{x,t}$ is the weight in the stocks measured in currency f. The restriction implies that the investor cannot use the forward contracts for currency speculation but only hedging. If $w_{f,t} = -w_{x,t}$, the investor is fully hedged and $w_{f,t} = 0$ corresponds to an unhedged portfolio. The optimal weights in currency forward contracts are given as:

$$\begin{aligned} w_{f,t}^* &= \max_{w_{f,t}} \begin{pmatrix} w_{x,t} \\ w_{f,t} \end{pmatrix}' \begin{pmatrix} \mu_{x,t+1} \\ \mu_{f,t+1} \end{pmatrix} - \frac{\gamma}{2} \begin{pmatrix} w_{x,t} \\ w_{f,t} \end{pmatrix}' \begin{pmatrix} \Sigma_{xx,t} & \Sigma_{fx,t}' \\ \Sigma_{fx,t} & \Sigma_{ff,t} \end{pmatrix} \begin{pmatrix} w_{x,t} \\ w_{f,t} \end{pmatrix}, \\ w_{f,t}^* &\leq 0, \\ w_{f,t}^* &\geq -w_{x,f}, \end{aligned} \tag{21}$$

where $\mu_{x,t+1}$ and $\mu_{f,t+1}$ is the expected return vector of the underlying stocks and forward contracts, respectively. $\Sigma_{xx,t}$ denotes the conditional covariance matrix of the international stocks, $\Sigma_{fx,t}$ is the conditional covariance matrix between the returns of the international stocks and returns of the forward contracts, and $\Sigma_{ff,t}$ is the conditional covariance matrix of the forward contracts. Equation (21) is solved numerically. We focus on the implications of return predictability established earlier and estimate the covariance matrices using a 60-month window. Furthermore, the choice of $w_{f,t}^*$ is independent of $\mu_{x,t}$. $\mu_{f,t+1}$ is given as the excess return forecasts from Section 5.3.

6.2. Data

We consider a cross-section consisting of the G10 currencies: Australia, Canada, Japan, Germany, Norway, New Zealand, Sweden, Switzerland, and the UK. The MSCI indices for these countries, sourced from Bloomberg, will serve as the stock components in the portfolio optimization problem. For the currency forwards, we use the data described in Section 3.

6.3. Results

Using monthly rebalancing, we evaluate the out-of-sample portfolio performance by the metrics; Sharpe ratio, Sortino ratio, and certainty equivalence. The performance is compared to three benchmarks; a portfolio in which a random walk is used to forecast the Dollar factor and two portfolios in which the currency risk is un- and fully hedged, respectively. We report the performance fee denoted as the fee a mean-variance investor is willing to pay to switch from a benchmark portfolio to the portfolio utilizing VPI-based forecasts for the optimal hedge position. For the analysis, we set the relative risk aversion, γ, equal to five, a common choice in literature.[10] Finally, we also estimate portfolio skewness and kurtosis. The portfolio performance is evaluated from January 2005 to December 2019 given the initial estimation period. Table 12 presents the results.

Table 12 about here

The dynamic hedged VPI-based portfolio (first column) delivers a higher average return (roughly 2.3% to 2.7% in excess), Sharpe- and Sortino ratios than the three benchmarks. The certainty equivalence is also higher, and an investor with mean-variance preferences is willing to pay between 203 and 300 annual basis points for switching from the benchmark portfolios to the VPI-based hedged portfolio. The superior performance is obtained without negatively impacting higher-order moments, as the VPI-based hedge portfolio has the least negative skewness and a lower kurtosis. Overall, our results show

[10]We find quantitatively similar results by setting γ equal to three and ten.

that in the context of hedging FX exposure, we find sizeable gains to harvest by exploiting the predictive power of VPI.

7. Robustness

This section presents evidence that the predictive power of VPI cannot be explained by traditional factors related to global risk and macroeconomic variables. First, we investigate the link between global risk factors known to have a link to exchange rates and VPI. Next, the section examines the link to macro variables, while it ends by examing longer-horizon returns.

7.1. VPI and global risk

The literature has, in general, found a tight link between global risk and currencies, see for instance Brunnermeier et al. (2008). VPI is related to general market risk, which motivates an examination of the link between VPI and other measures of risk applied in prior studies. We consider the following measures; the global financial cycle (GFC) factor of Miranda-Agrippino et al. (2020)[11], FX volatility innovations (ΔVOL_{FX}) as defined in Menkhoff et al. (2012), and the global economic policy uncertainty index (EPU) of Baker et al. (2016). Panel A of Table 13 reports the contemporaneous correlations between these uncertainty measures and VPI.

TABLE 13 ABOUT HERE

The absolute contemporaneous correlations between VPI and traditional measures of global risk from the literature are ranging between 0.09 and 0.25. More precisely, VPI has the highest correlation with the ΔVOL_{FX} (0.25) and a correlation of just 0.18 and -0.09 with the GFC and EPU measure, respectively. Table 14 presents the coefficients of Equation (13) and (12) controlling for each of the alternative measures of risk separately.

TABLE 14 ABOUT HERE

[11] The data is available at: https://silviamirandaagrippino.com/code-data until August 2019. The correlation and regression coefficients only use data up until this point

Compared to the results of Section 4.1, the coefficient on VPI is unaffected, and for all currency baskets, the coefficient on each of the controls is insignificant.

7.2. VPI and macro factors

The literature of risk premium in government bonds has examined the issue of unspanned macro risks and generally found that macro variables such as growth rates in industrial production contain information about bond risk premia (Ludvigson and Ng, 2009, Cooper and Priestley, 2009, Duffee, 2011, Joslin et al., 2014). Furthermore, Colacito et al. (2020) find that the output gap contains cross-sectional predictability about currencies. We now explore whether macro variables might help forecast the Dollar factor, potentially above and beyond what is captured by VPI. First, Panel B in Table 13 quantifies the correlation between VPI and; the growth rate in industrial production for the US, the industrial production growth in the U.S. minus the rest of world average, and the output gap for the U.S. minus the average foreign output gap defined for the same cross-section as VPI. We follow Colacito et al. (2020) and estimate each output gap by the methodology of Hamilton (2018) using a vintage dataset of industrial production from OECD. VPI is unrelated to all measures. The maximum absolute correlation is with the difference in IP growth rate between rest and U.S. of 0.27. Table 15 presents the results of including the macro factors as controls in Equation (13) and (12).

Table 15 about here

Overall, the coefficients and t-statistics are essentially unaffected by the inclusion of the macro factors, which, furthermore, all are insignificant. This suggests that macro factors cannot explain our findings.

7.3. Longer horizon returns

So far, we have focused on one-month returns and have not examined the predictive power at longer horizons. Table 16 presents the results based on 2-, 3-, 6-, 9-, and 12-month overlapping returns.

Table 16 about here

The predictive power of VPI is diminishing as the return horizon increases: the predicted Dollar factor movement of a one-standard deviation increase in VPI even switch sign for the longest forecast horizon. VPI is still a significant predictor for 2-months returns while the evidence is mixed for the 3-month returns. For all longer horizons, VPI is insignificant. The evidence for the longer horizons is consistent with our motivation: the predictive relationship between VPI and the Dollar factor is motivated by an Euler discretization of Equation (7). The approximation is less accurate for longer horizons. Given that the return horizon is different, we cannot compare the coefficients without an annualization. Figure 4 presents the annualized coefficients.

Figure 4 about here

The predicted effect on the Dollar factor of a one-standard deviation increase in VPI is monotonically decreasing in return horizon. In sum, VPI is only a powerful predictor of the Dollar factor for short-horizon returns.

8. Concluding remarks

We introduce variance risk premia imbalances (VPI) as a new predictor for the Dollar factor. VPI is defined as the difference between the variance risk premium in the U.S. and the average variance risk premium across nine developed economies.

We motivate VPI as a predictor by the no-arbitrage condition of Backus et al. (2001), also known as the asset market view of exchange rates. Short-horizon spot rate changes consist of two components: the difference in interest rates and the difference in SDF volatility (market-price of risk) between the two countries. We argue that VPI is a proxy for the latter term. In line with our theoretical motivation, VPI is a significant predictor of the Dollar factor at the one-month horizon for excess returns and spot rate changes. An increase in VPI predicts an appreciation (depreciation) of the Dollar factor (the USD). The predictive power of VPI preserves in bilateral exchange rates as well.

The predictive power of VPI remains out-of-sample. We show three different ways of how an investor can utilize the findings economically. First, a Dollar timing strategy based on the sign of VPI delivers significant excess returns and Sharpe ratios. Second, a long-short strategy of the portfolios that contain the currencies with the highest and lowest forecasted returns, respectively, earns excess returns and Sharpe ratios of similar magnitude to those obtained for equities. Third, an international investor receives sizeable economic gains by using VPI to optimize the hedge position in currency forward contracts.

VPI is uncorrelated with traditional factors of global economic risk and uncertainty. Controlling for these does not have any impact on our results.

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Table 1: 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

Table 2: Summary statistics of variance risk premium:
This table reports summary statistics of the VPI measure and country-specific VPs along with correlations. Eurozone VP is constructed as the GDP weighted average of the VPs of the eurozone countries (France, Germany, Italy, Netherlands). The VPI measure and the individual variance risk premiums 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 3: Predictability of the Dollar factor:

The 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 Hansen and Hodrick (1980) standard errors with one lag. 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	
			Excess returns			
Constant	0.12	10.50%	0.05	9.51%	0.15	10.72%
	[0.90]		[0.30]		[1.19]	
VPI	0.66		0.74		0.62	
	[3.09]		[3.25]		[2.96]	
			Spot returns			
Constant	-0.05	11.09%	0.04	9.41%	-0.09	11.37%
	[-0.36]		[0.26]		[-0.69]	
VPI	0.67		0.74		0.64	
	[3.27]		[3.26]		[3.2]	

Table 4: 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 5: Predictability of bilateral exchange rates: The 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 Hansen and Hodrick (1980) standard errors with one lag. 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 6: Predictability of the Dollar factor: The role of the foreign VP
The table presents the in-sample predictability results of Equation (13) and (12), in which we split VPI into a U.S. component and a foreign 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.

	Excess Ret		Spot rates	
	ψ	R^2	ζ	R^2
		All		
US	0.0033	11.49	0.0034	12.00
	[4.09]		[4.22]	
Rest	-0.0024		-0.0025	
	[-2.29]		[-2.42]	
Equal test	2.39		2.50	
	(0.12)		(0.11)	
		Developed		
US	0.0037	10.04	0.0037	9.90
	[4.24]		[4.22]	
Rest	-0.0030		-0.0030	
	[-2.44]		[-2.47]	
Equal test	0.89		0.89	
	(0.35)		(0.35)	
		Emerging		
US	0.0031	11.87	0.0032	12.50
	[3.89]		[4.06]	
Rest	-0.0022		-0.0023	
	[-2.23]		[-2.34]	
Equal test	3.55		3.89	
	(0.06)		(0.05)	

Table 7: Predictability of the Dollar factor: The role of VPI relative to currency variance risk premium

The table presents the in-sample predictability results of Equation (13) and (12), in which we control for the XVP measure of Londono and Zhou (2017). The table contains estimates of the coefficients, the degree of explained variation, and t-statistics calculated using Hansen and Hodrick (1980) standard errors with one lag 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	
			Excess returns			
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]	
			Spot changes			
Constant	-0.05	11.26%	0.04	9.41%	-0.09	11.74%
	[-0.36]		[0.26]		[-0.69]	
VPI	0.67		0.73		0.63	
	[3.26]		[3.26]		[3.20]	
XVP	0.08		0.01		0.12	
	[1.27]		[0.05]		[1.97]	

Table 8: Predictability of the Dollar factor: The role of VPI relative to average forward discount

The table presents the in-sample predictability results of Equation (13) and (12), in which we control for the average forward discount of Lustig et al. (2014). The table contains estimates of the coefficients, the degree of explained variation, and t-statistics calculated using Hansen and Hodrick (1980) standard errors with one lag 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	
			Excess returns			
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]	
			Spot returns			
Constant	-0.05	11.09%	0.03	9.56%	-0.08	11.46%
	[-0.36]		[0.22]		[-0.67]	
VPI	0.67		0.73		0.65	
	[3.24]		[3.24]		[3.18]	
AFD	-0.09		0.84		-0.52	
	[-0.08]		[0.61]		[-0.51]	

Table 9: Predictability of the Dollar factor out-of-sample:
The table displays the out-of-sample evidence of Dollar factor predictability. Panel A presents the Out-of-sample R^2 of Campbell and Thompson (2008) against the benchmark of, a random walk and a random walk with drift, respectively, for the Developed basket. 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 for whether our measure generates better forecasts than the benchmark are shown in parenthesis. Panel B presents the results of the VPI Dollar strategy. The strategy is long (short) the Dollar factor when VPI is positive (negative). The table shows mean return, Sharpe ratio (SR) for the strategy, in addition to t-statistics of the mean return being equal to 0. The sample spans from February 2000 to December 2019. Panel C presents the same measures as Panel B for the strategy of buying the Dollar factor in all periods. All standard errors in the table are calculated using Newey and West (1994) standard errors with six lags.

	Panel A: Out-of-sample performance	
Benchmark	Random walk with drift	Random walk
R^2_{OS}	12.51%	10.97%
	(0.03)	(0.02)
	Panel B: Dollar timing strategy	
	Developed	All
Return	4.10	3.12
	[2.47]	[2.23]
SR	0.50	0.44
	Panel C: Dollar factor	
Return	1.14	2.01
	[0.54]	[1.13]
SR	0.14	0.29

Table 10: Predictability of the bilateral exchange rates out-of-sample: The table displays the out-of-sample evidence of bilateral exchange rate predictability. Panel A (Panel B) presents the Out-of-sample R^2 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 for whether our measure generates better forecasts than the benchmark are shown in parenthesis.

	AUD	CAD	JPY	NZD	NOK	SEK	CHF	GPB	EUR
				Panel A: Benchmark: Random walk					
R^2_{OS}	9.22%	7.34%	-9.40%	10.88%	8.99%	9.92%	4.11%	12.89%	6.36%
	(0.02)	(0.03)	(0.82)	(0.01)	(0.03)	(0.03)	(0.02)	(0.06)	(0.02)
				Panel B: Benchmark: Random walk with drift					
R^2_{OS}	10.39%	8.94%	-6.07%	12.21%	10.73%	11.05%	6.02%	15.31%	7.43%
	(0.05)	(0.05)	(0.78)	(0.03)	(0.04)	(0.04)	(0.02)	(0.06)	(0.03)

Table 11: Currency portfolios sorted on OoS forecasts

The table reports the average return and Sharpe ratio for each portfolio j. t-statistics by Newey and West (1994) standard errors (six lags) are provided in brackets. The portfolios are rebalanced end-of-month. P1 (P5) contains the currencies with the lowest (highest) predicted returns, cf. Section 5.3. H-L denotes the strategy, which is long P5 and short P1.

	P1	P2	P3	P4	P5	H-L
			All countries			
Mean	-0.91	-1.06	1.08	1.96	3.22	4.13
	[-0.41]	[-0.46]	[0.47]	[1.00]	[1.29]	[2.33]
SR	-0.11	-0.13	0.14	0.25	0.36	0.54
			Developed countries			
Mean	-2.62	-0.95	-0.87	0.27	2.12	4.74
	[-1.12]	[-0.33]	[-0.35]	[0.11]	[0.79]	[2.51]
SR	-0.29	-0.10	-0.09	0.03	0.20	0.47

Table 12: Currency hedging strategies: a U.S. investor's perspective

The 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 is for the random walk approach, the third and fourth 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.

	DCH_{VP}	DCH_{RW}	Un-hedged	Full-hedged
Average return	6.86	4.53	4.21	4.48
STD	0.15	0.12	0.17	0.13
SR	0.46	0.37	0.25	0.36
Sortino	0.67	0.50	0.35	0.48
Skewness	-0.44	-0.88	-0.76	-0.90
Kurtosis	5.89	6.16	6.64	6.14
CEV	0.04	0.02	-0.00	0.02
Performance fee ($\gamma = 5$)	-	2.03	3.00	2.10

Table 13: VPI and alternative measures

The table presents correlations between VPI and alternative measures identified in the literature. The correlations are calculated using data from January 2000 to December 2019.

	Global risk measures				Macro factors		
	XVP	GFC	VOL_{inno}	EPU	Δ IP_{US}	Δ IPI	GAPI
VPI	0.11	0.18	-0.25	-0.09	-0.00	0.27	-0.10

Table 14:

Predictability of the Dollar factor: The role of VPI relative to Global risk

The table presents the in-sample predictability results of Equation (13) and (12), controlling for measures of global risk which are: the Global risk factor of Miranda-Agrippino et al. (2020), FX volatility innovations, as defined in Menkhoff et al. (2012) and the global policy uncertainty index (EPU) of Baker et al. (2016). The table contains estimates of the coefficients, the degree of explained variation, and t-statistics calculated using Hansen and Hodrick (1980) standard errors with one lag 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	
			Excess returns			
Constant	0.12	11.92%	0.05	11.05%	0.15	11.98%
	[0.85]		[0.28]		[1.11]	
VPI	0.7		0.8		0.66	
	[3.39]		[3.64]		[3.21]	
GFC	-0.22		-0.29		-0.18	
	[-1.27]		[-1.49]		[-1.08]	
Constant	0.12	10.89%	0.05	9.56%	0.15	11.36%
	[0.88]		[0.29]		[1.16]	
VPI	0.63		0.73		0.59	
	[3.02]		[3.13]		[2.94]	
$\Delta\sigma_{FX}$	-1.5		-0.67		-1.79	
	[-1]		[-0.49]		[-1.12]	
Constant	0.12	10.52%	0.05	9.59%	0.15	10.72%
	[0.9]		[0.3]		[1.19]	
VPI	0.66		0.74		0.62	
	[3.09]		[3.23]		[2.97]	
EPU	-0.03		-0.07		-0.01	
	[-0.3]		[-0.6]		[-0.07]	
			Spot changes			
Constant	-0.06	12.07%	0.03	10.84%	-0.1	12.15%
	[-0.43]		[0.2]		[-0.76]	
VPI	0.71		0.79		0.67	
	[3.49]		[3.62]		[3.35]	
GFC	-0.17		-0.28		-0.12	
	[-0.98]		[-1.42]		[-0.73]	
Constant	-0.05	11.68%	0.04	9.5%	-0.1	12.35%
	[-0.41]		[0.24]		[-0.77]	
VPI	0.64		0.72		0.6	
	[3.19]		[3.13]		[3.18]	
$\Delta\sigma_{FX}$	-1.83		-0.87		-2.23	
	[-1.25]		[-0.63]		[-1.45]	
Constant	-0.05	11.09%	0.04	9.44%	-0.09	11.37%
	[-0.36]		[0.26]		[-0.69]	
VPI	0.67		0.73		0.64	
	[3.27]		[3.25]		[3.21]	
EPU	-0.01		-0.04		0.01	
	[-0.11]		[-0.38]		[0.05]	

Table 15: Predictability of the Dollar factor: The role of VPI relative to macroeconomic conditions The table presents the in-sample predictability results of Equation (13) and (12), controlling for the macro factors: the growth rate in industrial production for the U.S., the industrial production growth in the U.S. minus the average foreign (Δ IPI), and the output gap for the U.S. minus the average foreign output gap (GAPI). We follow Colacito et al. (2020) and estimate each output gap by the methodology of Hamilton (2018) using a vintage data set of industrial production from OECD. The table contains estimates of the coefficients, the degree of explained variation, and t-statistics calculated using Hansen and Hodrick (1980) standard errors with one lag 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	
			Excess returns			
Constant	0.16	11.73%	0.09	10.76%	0.19	11.9%
	[1.1]		[0.55]		[1.36]	
VPI	0.71		0.81		0.67	
	[3.44]		[3.65]		[3.29]	
Δ IP$_{US}$	-5.49		-6.55		-4.99	
	[-1.24]		[-1.38]		[-1.17]	
Constant	0.13	11.59%	0.05	10.55%	0.16	11.74%
	[0.94]		[0.33]		[1.23]	
VPI	0.66		0.74		0.62	
	[3.26]		[3.41]		[3.12]	
Δ IPI	-8.63		-10.01		-7.76	
	[-1.18]		[-1.25]		[-1.11]	
Constant	0.12	11.76%	0.05	10.99%	0.15	11.6%
	[0.92]		[0.31]		[1.21]	
VPI	0.68		0.77		0.64	
	[3.18]		[3.37]		[3.02]	
GAPI	0.23		0.29		0.18	
	[1.78]		[1.9]		[1.53]	
			Spot changes			
Constant	-0.02	11.72%	0.08	10.51%	-0.07	11.76%
	[-0.15]		[0.49]		[-0.5]	
VPI	0.71		0.79		0.67	
	[3.54]		[3.63]		[3.43]	
Δ IP$_{US}$	-3.91		-6.13		-2.91	
	[-0.89]		[-1.29]		[-0.68]	
Constant	-0.05	11.89%	0.04	10.25%	-0.09	12.11%
	[-0.34]		[0.28]		[-0.68]	
VPI	0.67		0.73		0.64	
	[3.42]		[3.41]		[3.35]	
Δ IPI	-7.36		-8.93		-6.66	
	[-1.04]		[-1.1]		[-0.99]	
Constant	-0.05	12.15%	0.04	10.87%	-0.09	12.17%
	[-0.36]		[0.26]		[-0.7]	
VPI	0.69		0.77		0.66	
	[3.35]		[3.38]		[3.26]	
GAPI	0.21		0.29		0.17	
	[1.66]		[1.89]		[1.46]	

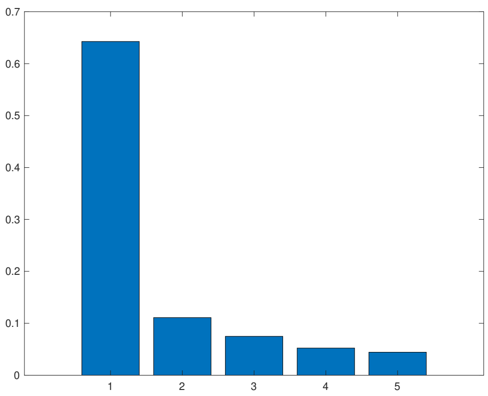
Table 16: Predictability of the Dollar factor: Longer horizon returns

The table presents the VPI slope coefficients and regression R^2s using excess returns (top panel) and spot rate changes (bottom panel) across the three currency-baskets: All, Developed and Emerging. The t-statistics are calculated using Hansen and Hodrick (1980) standard errors with lag length equal to the forecast horizon.

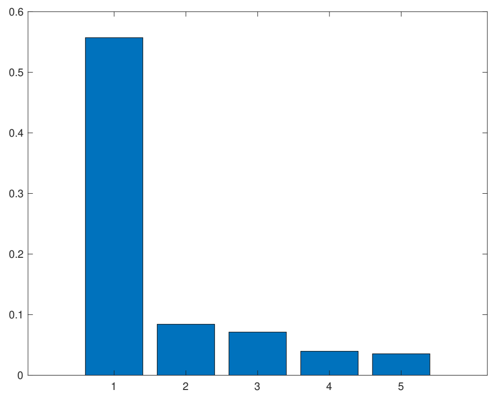
Horizon	Coefficients	R^2	Coefficients	R^2	Coefficients	R^2
	All		Developed		Emerging	
			Excess returns			
2	0.61	4.19%	0.60	2.99%	0.62	4.88%
	[2.45]		[2.81]		[2.01]	
3	0.61	2.62%	0.53	1.48%	0.66	3.45%
	[1.88]		[1.76]		[1.91]	
6	0.45	0.64%	0.21	0.11%	0.58	1.15%
	[1.45]		[0.52]		[1.27]	
9	0.02	0%	-0.26	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]	
			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]	

Figure 1: PCA factors and the degree of explained total variation

This figure shows the degree of explained variation by the first five PCA factors for a cross section of developed currencies (a) and all currencies (b).



(a) Developed



(b) All

Figure 2: VPI

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

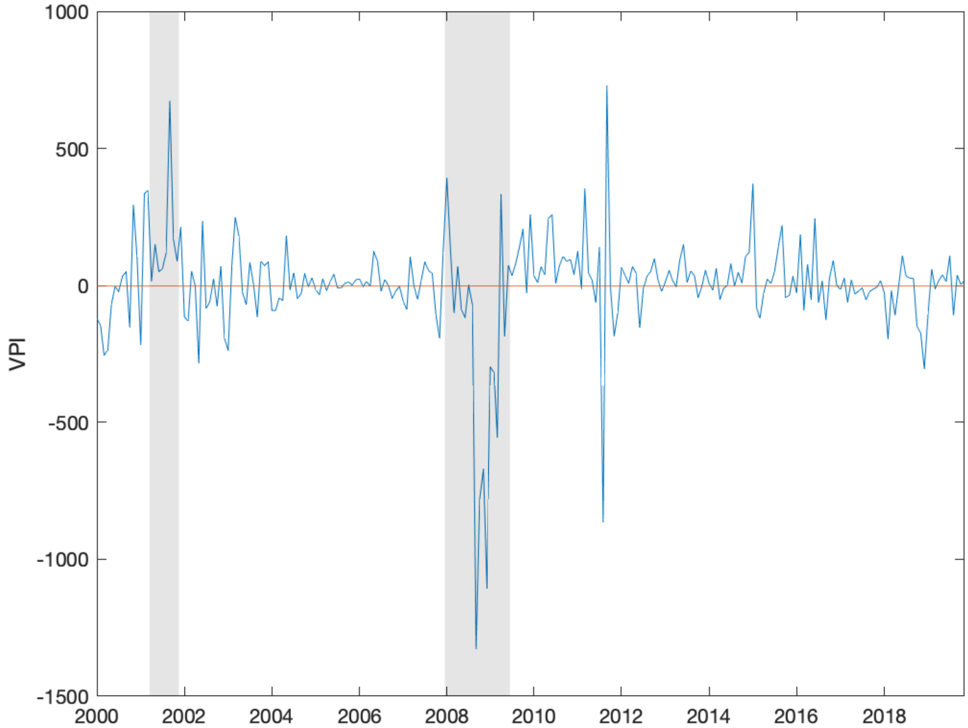
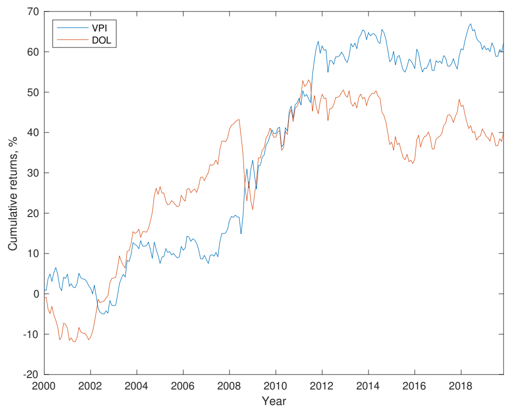


Figure 3: The VPI Dollar strategy: cumulative returns

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.

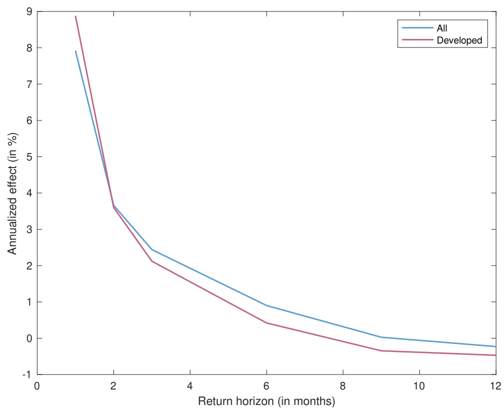


(a) All

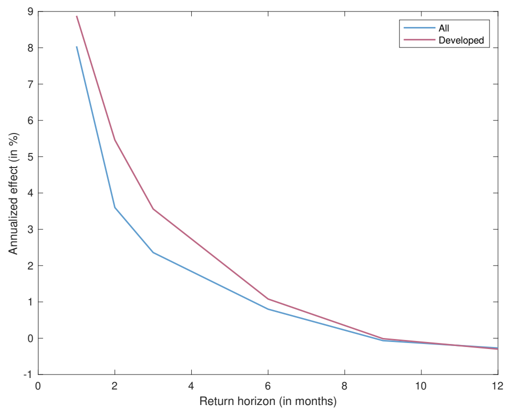
(b) Developed

Figure 4: 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