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Skewness Risk Premia and the Cross-Section of Currency Returns *

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Abstract

Using model-free skewness measures that exploit the asymmetry in semivariances and option data from the over-the-counter currency market, we find that buying currencies with a high skewness risk premium (SRP) and selling currencies with a low SRP generates high returns and Sharpe ratio. Asset pricing tests – which control for omitted variables and measurement errors – show that a SRP factor enters the currency pricing kernel and is central to the pricing of risks inherent in a broad currency cross-section of 60 portfolio excess returns. These results imply that skewness risk is a strong and priced source of currency risk.

Keywords: Currency risk premia, asset pricing, skewness risk, crash risk, stochastic discount factor.

JEL Classification: F31; G12; G15.

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1. Introduction

Extreme but rare events, such as the global financial crisis (GFC) and the Covid-19 pandemic, had profound effects on the global economy and led to sharp corrections in international capital flows and asset prices (see, e.g., OECD, 2020; Goldstein, Koijen, and Mueller, 2021). Investors' expectations about financial markets are heavily shaped by what happens during these extreme circumstances (e.g., Bianchi, 2020). Consistently, disaster or crash risk is a prominent feature of many asset pricing models (see, e.g., Rietz, 1988; Barro, 2006, 2009; Gourio, 2012; Gabaix, 2012; Wachter, 2013), and exchange rate determination models are no exception (e.g., Farhi and Gabaix, 2016).[1]

In their theory, Farhi and Gabaix (2016) show that investing in high interest-rate currencies yields an unconditionally positive expected excess return that compensates for disaster risk. Moreover, Liao and Zhang (2024) show that systematic variation in hedging demand and intermediary constraints help rationalize large exchange rate movements observed during times of financial distress. Such exchange rate fluctuations reflect currency crash risk for countries with negative external imbalances (independently of their interest rates), for which investors demand compensation in equilibrium. At the same time, a large body of finance literature (reviewed below and dating back at least to the seminal paper of Arditti (1967)) assigns a specific role to skewness risk in determining asset prices.

Motivated by this literature, the goal of this paper is to assess empirically the relation between currency excess returns and skewness risk for a broad cross-section of currency strategies and exchange rates, covering both developed and emerging economies. The breadth of the cross-section of test assets is key to assess the strength of skewness risk beyond carry trade strategies, and hence for the overall currency market. In essence, we address two questions. First, does the cross-currency variation in skewness risk premia embed predictive information for the cross-section of currency portfolio excess returns? Second, is skewness risk priced in the currency market?[2]

While crash risk is notoriously hard to measure due to its intrinsic nature of being rare (e.g., Baron, Xiong, and Ye, 2024), out-of-the-money options embed highly valuable

[1]Asset prices can well reflect the skewness risk in the economy (e.g., see Dew-Becker, Giglio, and Kelly, 2021). Indeed recessions are a defining feature of the business cycle making it inherently asymmetric or left-skewed, being characterized by large and negative fluctuations in output (e.g., Morley and Piger, 2012; Salgado, Guvenen, and Bloom, 2019; Dew-Becker, Tahbaz-Salehi, and Vedolin, 2021). Moreover, Muir (2017) documents that risk premia increase more during recessions and financial crises than during wars, while Baron, Xiong, and Ye (2024) provide evidence that asset prices might only slowly incorporate objective disaster risk.

[2]In what follows, we use interchangeably the terms: skewness risk, tail risk, disaster risk, and crash risk. We treat these terms as synonyms because we are not interested in disentangling, e.g., the difference between skewness risk (a pure measure of third moment risk) and crash risk (a broader concept than just the third moment). We are interested in learning about crash risk without being too concerned about measuring directly the third moment.

information about rare events (e.g., Carr and Wu, 2007; Bollerslev and Todorov, 2011). In this regard, it is particularly informative to focus on the slope of the implied volatility surface (e.g., Bakshi, Kapadia, and Madan, 2003), as measured for example by the asymmetry in the semivariances, which is easy to construct and interpret (e.g., Feunou, Jahan-Parvar, and Okou, 2018; Kilic and Shaliastovich, 2019; Bollerslev, 2021). In turn, the wedge between realized and option-implied measures of asymmetry is informative about changes in market-wide perceptions of skewness risks and risk aversion, and has been shown to have predictive power for equity returns (e.g., Feunou et al., 2018; Kilic and Shaliastovich, 2019). We build on this literature but shift the focus to the foreign exchange market, and construct model-free measures of currency risk-neutral (i.e., from currency options) and objective (i.e., from currency returns) skewness from semivariances. For a given currency, we then construct the skewness risk premium (SRP) as the wedge between the two normalized objective and risk-neutral measures.[3]

We consider up to 28 currencies defined with respect to the U.S. Dollar, sampled at monthly frequency over the 1998-2021 period, which is dictated by the option data available. This currency universe constitutes a relatively large cross-section of individual currencies, including both safe and emerging currencies for which currency spot and option contracts are actively traded. We find that currency skewness risk premia – which capture the costs of insurance against fluctuations in the skewness of the underlying currency – are positive on average but display substantial variation across time and currencies. Intuitively, this evidence is consistent with the notion that investors dislike currency skewness risk and are willing to pay a premium to insure against skewness fluctuations.[4]

We then dynamically allocate, in real time, currencies into portfolios based on their SRPs. We find that the resulting long-short trading strategy (which we dub SRP_{HML}) that buys the top quintile portfolio of currencies with high SRPs and shorts the bottom quintile portfolio of currencies with low SRPs, is highly profitable, delivering a large average excess return and Sharpe ratio. Consistent with Farhi and Gabaix (2016) and similar to the carry trade strategy, the performance of the SRP_{HML} strategy is driven primarily by the interest-rate differentials instead of currency spot returns. SRP_{HML} excess returns are negatively skewed, displaying large drops during market crashes, like the GFC and the market turmoil triggered by the outbreak of the Covid-19 pandemic.

In addition to SRP portfolios, we also construct several other portfolios based on option information, including portfolios sorted on risk reversals and the variance risk

[3]The normalization simply involves dividing by the total variance, and it is needed to satisfy the conditions required by any skewness measure, as discussed formally later in the paper.

[4]In this paper, we define the exchange rate as the U.S. Dollar price of the foreign currency, so that when the exchange rate decreases, the foreign currency depreciates relative to the U.S. Dollar. Thus, a positive skewness risk premium is consistent with investors pricing an even larger depreciation in the foreign currency under the risk-neutral than under the objective measure.

premium studied in prior literature (e.g., Della Corte, Ramadorai, and Sarno, 2016), as well as novel option-based signals derived from upside and downside semivariances. This gives rise to a rich set of option-based currency investment strategies which are pooled together with a variety of currency strategies proposed in previous studies, generating a very broad cross-section of 60 test asset returns. The marginal contribution of option-based strategies to the risk-return trade-off in currency markets proves to be strongly positive, in the sense that their inclusion leads to a superior efficient frontier and therefore to a substantial improvement in the Sharpe ratio of the tangency portfolio. Nevertheless, among these option-based strategies, SRP singles out as it yields the highest Sharpe ratio and the strongest marginal contribution to the efficient frontier.

A major result of the paper is that SRP_{HML} is a strong slope risk factor as it helps price many currency investment strategies, not just carry. Figure 1 illustrates this in a simple, model-free manner. Essentially all the currency investment strategies considered, which rely on a variety of signals (e.g., carry, past returns, value, and option-based risk premia), clearly yield higher excess returns when SRP_{HML} is high, and vice versa. These patterns in returns are often monotonic, suggesting strong linear relationships. Hence, SRP_{HML} appears to be tightly linked with these investment strategies. The association is, however, weaker for short-term momentum, especially when SRP_{HML} returns are low; this is not surprising given that short-term momentum tends to perform relatively well during crisis and has positively skewed returns. In the empirical analysis, we will show that these results arise also in formal asset pricing tests.

While we employ a variety of asset pricing tests, our baseline results are obtained using the recently developed three-pass procedure (Giglio and Xiu, 2021). This is desirable for several reasons. First, while a large cross-section of test assets is crucial for the validity of asset pricing tests (Lewellen, Nagel, and Shanken, 2010), it raises the bar significantly in terms of specifying a pricing kernel or stochastic discount factor (SDF) that fully prices the cross-section of test assets. Put simply, the omitted-variable problem that affects standard asset pricing methods becomes more relevant the larger the cross-section of test assets. Second, candidate pricing factors in the SDF are well-known to be contaminated by measurement error. For tradable factors measurement error could reflect exposures to unpriced risk (e.g., non-diversifiable errors in the portfolio), or idiosyncratic risk that is not fully diversified (Daniel, Mota, Rottke, and Santos, 2020; Giglio and Xiu, 2021; Giglio, Xiu, and Zhang, 2024). The three-pass procedure allows us to tackle both problems, by obtaining robust risk-premium estimates of potential currency risk factors, either tradable or nontradable.

Therefore, we recur to the Risk-Premium Principal Component Analysis (RP-PCA) three-pass estimator, which combines the three-pass estimator developed by Giglio and Xiu (2021), with the RP-PCA estimator of Lettau and Pelger (2020). The RP-PCA method, recently employed by Nucera, Sarno, and Zinna (2024) to achieve robust esti-

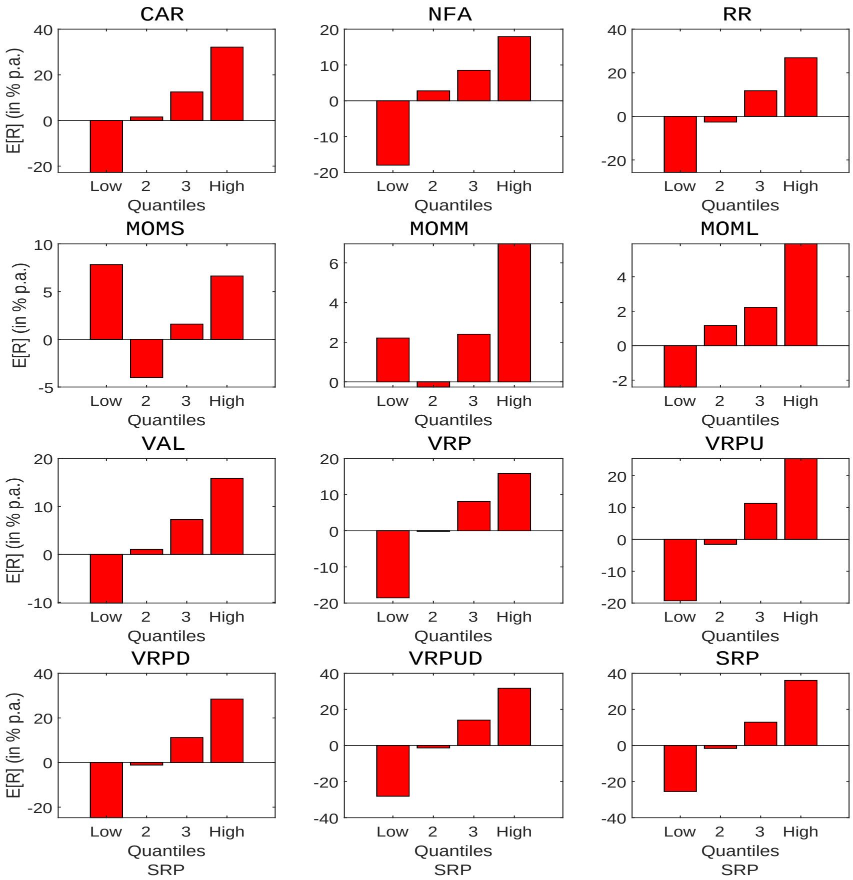

Figure 1: Currency Investment Strategies and the SRP HML Factor

The figure shows mean excess returns for the HML factors of the 12 currency investment strategies conditional on the SRP_{HML} factor being within the lowest and highest quartile of its sample distribution (four categories from lowest to highest shown on the x-axis of each panel). Specifically, in addition to the SRP_{HML} factor, we consider the HML factors associated with the following 11 currency investment strategies: carry (CAR), net-foreign assets (NFA), risk-reversal (RR), short-, medium-, and long-term momentum (MOMS, MOMM, and MOML, respectively), value (VAL), variance risk premium (VRP), upside variance, downside variance, and asymmetric variance risk premium (VRPU, VRPD, and VRPUD, respectively). We provide a detailed description of the currency strategies in the Internet Appendix (Section III). The sample spans the period from February 1998 to December 2021 at monthly frequency ($T = 287$).

mates of currency risk premia, allows us to efficiently recover the latent-factor SDF from the panel of currency portfolios (test assets), ensuring that all portfolio returns are priced and no alpha is left unexplained. In turn, the resulting latent-factor SDF is then the key input to achieve robust estimates of candidate factors' risk premia via the three-pass method. The procedure also delivers de-noised factors, which are obtained by projecting the raw candidate factors onto the latent factors that comprise the optimal SDF. In essence, this regression cleans the candidate pricing factors from measurement errors and/or unpriced risks. This means that the de-noised factors can be interpreted as the excess returns associated with the candidate factor that can be expected in equilibrium on the basis of the latent-factor SDF.

The three-pass analysis delivers a number of clearcut results. First, the currency SDF consists of seven latent factors. This is a larger model than the one uncovered by Nucera et al. (2024), which is not surprising given that the cross-section of test asset returns has expanded considerably with the addition of option-based portfolio returns. Second, using this seven-factor model, the HML factors with statistically significant average returns also tend to have significant risk-premium estimates. The risk-premium estimates are close to the sample means of the factors for many of the HML factors, but not for all of them. Specifically, the SRP_{HML} risk-premium estimate is close to the model-free estimate given by its mean (5.47% vs. 5.35%); however, the Sharpe ratio of the de-noised SRP_{HML} factor increases relative to the raw factor from 0.75 to 0.82. Third, the analysis confirms that SRP_{HML} is a strong slope factor, being driven almost entirely by the priced sources of currency risk. The analysis confirms a close association between SRP_{HML} and the carry factor, and a much weaker but non-negligible relation between SRP_{HML} and momentum strategies.

We attempt to price the full cross-section of 60 portfolio excess returns with low-dimensional SDFs that include de-noised factors. Specifically, we use the de-noised HML factors in standard two-pass and GMM asset pricing tests, in order to provide robust evidence about the strength and information content of the SRP factor. This analysis shows that even a simple three-factor model including a Dollar level factor and two SRP and momentum slope factors prices the full cross-section of 60 test assets very accurately.

Additional analysis confirms the close association between SRP_{HML} and the carry factor. However, the three-pass procedure reveals that the CAR excess return is driven partly by unpriced risk and that the excess return of de-noised CAR displays a lower Sharpe ratio than de-noised SRP_{HML}. Moreover, it makes clear that, while SRP_{HML} and CAR are highly correlated, SRP displays stronger pricing power than CAR and fully subsumes the information in CAR. Furthermore, we show that the asset pricing results are generally robust to replacing the SRP_{HML} factor with its nontradable counterpart, SRP_{NT} – the innovation to the time series of cross-sectional standard deviations of the monthly currency SRP signals. This result is interesting because nontradable factors perform notoriously less well than tradable factors in asset pricing tests, yet they should connect more directly with primitive economic sources of macro-financial risk. Finally, we subject the results to a number of robustness checks, none of which invalidates the above claims.

`Remainder.` The paper proceeds as follows. Section 2 reviews the related literature. Section 3 introduces the model-free measures of currency variance and skewness risk premia. Section 4 presents the FX data, portfolios and factors. Section 5 shows the key findings from applying the three-pass method and from implementing conventional asset pricing tests on de-noised factors. Section 6 briefly presents some robustness checks. Section 7 concludes the paper. Additional material and empirical analysis are presented in the Internet Appendix.

2. Related Literature

This paper contributes and relates to several strands of the asset pricing literature. Above all, it connects with the vast and rapidly evolving international finance literature on exchange rates and currency returns. Since the pioneering study of Lustig and Verdelhan (2007), this literature has documented a number of profitable currency cross-sectional investment strategies. The most prominent canonical strategies are currency carry (e.g., Lustig, Roussanov, and Verdelhan, 2011; Burnside et al., 2011, Menkhoff et al., 2012a; Lettau, Maggiori, and Weber, 2014; Koijen et al., 2018), currency momentum (e.g., Burnside, Eichenbaum, and Rebelo, 2011; Menkhoff et al., 2012b, Asness, Moskowitz, and Pedersen, 2013, Zeng, 2023), and currency value (e.g., Asness, Moskowitz, and Pedersen, 2013; Kroencke, Schindler, and Schrimpf, 2014; Menkhoff et al., 2017). However, over time other strategies have been shown to be profitable and imperfectly correlated with these canonical strategies (e.g., Della Corte, Ramadorai, and Sarno, 2016; Della Corte, Riddiough, and Sarno, 2016; Colacito, Riddiough, and Sarno, 2020; Dahlquist and Hasseltoft, 2020; Andrews, Colacito, Croce, and Gavazzoni, 2024).

Until recently, however, common practice has mainly been to study the risk profile of these strategies separately, relying on rather small cross-sections, which in turn constrain the number of candidate risk factors, either tradable or nontradable, entering the SDF (e.g., Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a). Moreover, this literature has mostly focused on explaining the carry risk premium, given that carry was the most prominent slope risk factor entering the SDF. From the onset, carry appeared as a highly profitable but risky strategy being subject to crash risk, and hence with highly left-skewed returns (Brunnermeier, Nagel, and Pedersen, 2008).[5] Indeed carry trade returns co-move with risk reversals – a simple and yet readily available option-based measure of crash risk – of riskier countries (Farhi et al., 2015). Meanwhile, high risk-reversal countries tend to have both higher interest rates (e.g., Du, 2013) and currency expected returns (e.g., Farhi et al., 2015), and their currencies depreciate when their risk reversal goes up (Carr and Wu, 2007). These facts, taken together, lend support to the predictions of the rare disaster model of Farhi and Gabaix (2016). By looking at hedged and unhedged carry trade returns, Burnside et al. (2011) argue that crash risk accounts almost entirely for the carry risk premium, while using a similar methodology Jurek

[5]It is common to hear that the currency carry trade is tantamount to picking up pennies in front of a steamroller (e.g., Pedersen, 2015).

(2014) quantifies its impact in the order of one third.[6] The relevance of crash/skewness risk in explaining carry returns also emerges from parametric models that feature jumps in the exchange rate dynamics (see, e.g., Carr and Wu, 2007; Bakshi, Carr, and Wu, 2008; Chernov, Graveline, and Zviadadze, 2018). Other papers propose alternative versions of carry with reduced skewness risk (see, e.g., Daniel, Hodrick, and Lu, 2017; Bekaert and Panayotov, 2020). Yet, other studies measure downside risk (Lettau, Maggiori, and Weber, 2014; Dobrynskaya, 2014) and tail risk (Fan, Londono, and Xiao, 2022) in the U.S. equity market and show that these measures can help price carry returns (and other strategies).[7] Our paper is related to this literature but we are not concerned with measuring the cost of hedging crash risk and the reduction in carry returns induced by buying such hedge. Instead, our focus is on constructing a skewness risk factor in foreign exchange markets and evaluating its pricing performance on a broad set of currency investment strategies rather than only on carry portfolios.

A recent paper by Chernov, Dahlquist, and Lochstoer (2023) examines the pricing properties of a SDF constructed from the cross-section of G10 currency returns. They characterize expected returns, both unconditionally and conditionally, using only a few signals – carry, momentum and value – and find that a large fraction of test-asset returns is unpriced. In this paper, we study a large cross-section of currency portfolio returns using both traditional two-pass and recently developed three-pass methods that allow for a comprehensive analysis of the risk-return tradeoff inherent in currency strategy returns, accounting for potential omitted variables in the SDF. By applying the three-pass method to a cross-section of currency portfolios, Nucera et al. (2024) show that at least three and potentially four latent factors should enter the currency SDF. The dominant latent factors relate to carry and short-term momentum, while the evidence for a fourth value-like latent factor is weaker. However, they do not consider either option-based currency strategies in their set of test assets or specific measures of crash risk (premia) in the list of candidate risk factors, which are central to our study. Therefore, while we also employ the three-pass method in the empirical analysis, our data and objectives are substantially different from theirs, and the broader set of test assets studied here poses a more difficult challenge to recover a parsimonious SDF. Liu, Maurer, Vedolin, and Zhang (2024) finds that, in a conditional setting, the currency pricing models could become even more parsimonious.

[6] An unpublished paper by Rafferty (2012) constructs a nontradable global skewness risk factor by aggregating the realized skewness of individual currencies, whereby the sign of realized skewness for each currency is normalized depending on whether the currency is a funding or an investment currency (i.e., depending on the currency forward discount). This global realized measure of realized skewness is priced in currency carry portfolios, but has less success in pricing momentum and value portfolios. Our analysis differs from that of Rafferty (2012) in a number of important ways. Above all, we compute skewness measures using semivariances, using information in currency options and spot returns. Moreover, our evidence is uncovered using a much broader cross-section of currency portfolios, employing both conventional and more recent asset pricing tests, and also using a tradable skewness risk factor.

[7] Londono and Zhou (2017) show that the U.S. equity variance risk premium helps predict currency returns.

A related currency option-based strategy is the volatility-risk-premium strategy of Della Corte, Ramadorai, and Sarno (2016). We show that the performance of this strategy deteriorates when extending their sample period, possibly because it combines two distinct sources of risks (i.e., downside and upside semivariances) that are better captured by our SRP measure.[8] Indeed, their strategy also appears to be weakly correlated with our proposed strategy, and with many of the other existing currency strategies. Thus, unlike SRP_{HML}, its appeal stems mainly from its diversification benefits, rather than from its profitability.

Second, while we do not present a formal theoretical model that links skewness risk (premia) to currency returns, the role of skewness risk in driving asset returns is well established in the literature (see, e.g., Arditti, 1967, 1971; Kraus and Litzenberger, 1976; Simkowitz and Beedles, 1978; Conine and Tamarkin, 1981; Scott and Horvath, 1980; Kane, 1982; Harvey and Siddique, 2000; Mitton and Vorkink, 2007).[9] Intuitively, investors have a preference for holding assets with positive skewness rather than negative skewness. This implies that, in equilibrium, assets with negatively (positively) skewed returns tend to command a positive (negative) risk premium.[10] Therefore, this vast literature on skewness naturally connects with the theories of rare disasters and asset prices mentioned earlier (e.g., Rietz, 1988; Barro, 2006, 2009; Gourio, 2012; Gabaix, 2012; Wachter, 2013) and in particular with Farhi and Gabaix (2016), who show how rare but extreme disasters can be an important determinant of currency risk premia and rationalize a positive average excess return from carry trades.[11]

3. Variance, Semivariance, and Skewness Risk Premia

In this section, we detail the construction of currency variance, semivariances, and skewness risk-premium signals, which are used as sorting variables in the cross-sectional analysis. The currency variance risk premium is defined as the difference between the expected objective ($\mathbb{P}$) and risk-neutral ($\mathbb{Q}$) variances of currency returns (see, e.g., Della Corte,

[8]Bollerslev, Todorov, and Xu (2015) reach a similar conclusion when dissecting the drivers of the equity variance risk premium. See also Bollerslev (2021) and references therein.

[9]This list is by no means exhaustive and is expanding over time. Moreover, a somewhat separate literature studies preference for skewness in a behavioral framework (e.g., Brunnermeier, Gollier, and Parker, 2007; Barberis and Huang, 2008; Kumar, 2009; Boyer, Mitton, and Vorkink, 2010). We refer to Jondeau, Zhang, and Zhu (2019) and Schneider, Wagner, and Zechner (2020), and the references therein.

[10]Kelly and Jiang (2014) construct a measure of systematic tail risk by exploiting the common fluctuation in firm-level price crashes, and find that it has predictive power for both the aggregate stock market return and the cross-section of average returns, as well as for real economic activity. Langlois (2020) shows that systematic skewness is relatively more important than idiosyncratic skewness in explaining differences in expected returns across stocks. See also Bollerslev (2021) for additional references on the pricing of downside, tail, and crash risks.

[11]Ready, Roussanov, and Ward (2017) develop and calibrate an exchange rate determination model allowing for the possibility of large jumps in productivity. This is interpreted as capturing rare disasters and allows the model to account for observed interest rate differentials and average returns of commodity currency carry trade.

Ramadorai, and Sarno, 2016, and references therein). Following the literature (see, e.g., Feunou, Jahan-Parvar, and Okou, 2018; Kilic and Shaliastovich, 2019), we construct the currency semivariances and skewness risk premia in a similar way, that is, as the differences between their respective expected $\mathbb{P}$ and $\mathbb{Q}$ measures. In general, it is common practice in the empirical asset pricing literature to measure risk premia as the difference between $\mathbb{P}$ and $\mathbb{Q}$ measures (see, e.g., Carr and Wu, 2008; Bollerslev, Tauchen, and Zhou, 2009). Therefore, the construction of moment risk premia requires $\mathbb{P}$ and $\mathbb{Q}$ estimates, which we describe next.

To start with, we measure variance of a currency at the end of month $t + \tau$ with the realized variance, defined as the summation of squared daily log returns of the spot exchange rate (S), expressed as units of domestic currency per unit of foreign currency, in the previous τ months,

$$RV_{t,t+\tau} = \frac{12}{\tau} \sum_{d=1/21}^{\tau} (r_{t+d})^2, \tag{1}$$

where $r_{t+d} = \ln(S_{t+d}/S_{t+d-1/21})$ denotes the daily spot return. In addition, following Barndorff-Nielsen, Kinnebrock, and Shephard (2010), we approximate its upside and downside semivariances as follows:

$$RV^U_{t,t+\tau} = \frac{12}{\tau} \sum_{d=1/21}^{\tau} (r_{t+d})^2 \mathbb{1}_{[r_{t+d}>0]}, \qquad RV^D_{t,t+\tau} = \frac{12}{\tau} \sum_{d=1/21}^{\tau} (r_{t+d})^2 \mathbb{1}_{[r_{t+d}\leq 0]}, \tag{2}$$

where $\mathbb{1}_{[r_{t+d}>0]}$ ($\mathbb{1}_{[r_{t+d}\leq 0]}$) is an indicator function that takes the value of 1 if r_{t+d} is greater (equal or lower) than zero, and zero otherwise. It then holds that $RV_{t,t+\tau} = RV^U_{t,t+\tau} + RV^D_{t,t+\tau}$.

By taking the difference between upside and downside semivariances, we obtain a measure of variance asymmetry,

$$RV^{U/D}_{t,t+\tau} = RV^U_{t,t+\tau} - RV^D_{t,t+\tau}, \tag{3}$$

which has been employed successfully by a number of recent studies for equity markets (see, e.g., Patton and Sheppard, 2015; Feunou, Jahan-Parvar, and Okou, 2018; Bollerslev, Li, and Zhao, 2020).[12]

[12] The measure of asymmetry in Eq. (3) is generally termed as "signed jump variation" in the high-frequency literature. This is because in-fill asymptotics ensures that the difference between positive and negative semivariances converges to the difference between positive and negative squared jumps, as the integrated variances cancel out (see, e.g., Bollerslev, Li, and Zhao, 2020). Therefore, using high-frequency returns, this interpretation of signed jump variation is exact, given that the effect of the price drift vanishes asymptotically. We discuss this issue further later on.

3.1. Risk-neutral ($\mathbb{Q}$) Expected Measures

We follow the model-free methods proposed by Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003) to infer expected risk-neutral measures from the cross-section of out-of-the-money currency options. Specifically, Bakshi and Madan (2000) show that any payoff function with bounded expectation on an asset can be spanned by a continuum of out-of-the-money (OTM) call and put prices contingent on that asset.

For the risk-neutral expectation of realized variance

$$IV_{t,t+\tau} \;=\; \mathbb{E}_t^{\mathbb{Q}}\Big[RV_{t,t+\tau}\Big], \tag{4}$$

where $\mathbb{E}_t^{\mathbb{Q}}$ defines the time-t conditional expectation under the risk-neutral measure $\mathbb{Q}$, Bakshi, Kapadia, and Madan (2003) show that $IV_{t,t+\tau}$ can be extracted from the OTM call and put option prices as follows

$$IV_{t,t+\tau} = \int_{S_t}^{\infty} \frac{2\Big(1-\log(\frac{K}{S_t})\Big)}{K^2} C(t,\tau;K)dK + \int_0^{S_t} \frac{2\Big(1+\log(\frac{S_t}{K})\Big)}{K^2} P(t,\tau;K)dK, \tag{5}$$

where S_t is the spot exchange rate, $C(t,\tau;K)$ and $P(t,\tau;K)$ represent call and put prices, and K is the corresponding strike price. IV_t is then the forward-looking expected risk-neutral variance over the next τ period, conditioning on information at time t.[13]

Furthermore, following the same approach, the risk-neutral expectations of upside and downside realized variances

$$IV^U_{t,t+\tau} = \mathbb{E}_t^{\mathbb{Q}}\Big[RV^U_{t,t+\tau}\Big] \qquad IV^D_{t,t+\tau} = \mathbb{E}_t^{\mathbb{Q}}\Big[RV^D_{t,t+\tau}\Big] \tag{6}$$

can be obtained as follows:

$$IV^U_{t,t+\tau} = \int_{S_t}^{\infty} \frac{2\Big(1-\log(\frac{K}{S_t})\Big)}{K^2} C(t,\tau;K)dK, \quad IV^D_{t,t+\tau} = \int_0^{S_t} \frac{2\Big(1+\log(\frac{S_t}{K})\Big)}{K^2} P(t,\tau;K)dK, \tag{7}$$

such that $IV_{t,t+\tau} = IV^U_{t,t+\tau} + IV^D_{t,t+\tau}$. A similar decomposition has been employed by Feunou, Jahan-Parvar, and Okou (2018) and Kilic and Shaliastovich (2019) for the stock market implied variance, and by Huang and Li (2019) for individual stock implied variances.

A forward-looking risk-neutral measure of currency variance asymmetry implied in

[13] A point that is often bypassed in using Eq. (5) is that in theory it can admit negative variances. However, this would only arise for very extreme values of OTM options. This is also why Bakshi, Kapadia, and Madan (2003) limit the moneyness in the range from 1/3 to 3. We apply the same restrictions on moneyness in our empirical work when constructing risk-neutral variance and semivariances (see Section I, in the Internet Appendix).

option prices can be easily obtained as follows:

$$IV^{U/D}_{t,t+\tau} = IV^{U}_{t,t+\tau} - IV^{D}_{t,t+\tau}. \tag{8}$$

We further normalize the asymmetry measure by the total implied variance,

$$ISK_{t,t+\tau} = \frac{IV^{U}_{t,t+\tau} - IV^{D}_{t,t+\tau}}{IV_{t,t+\tau}}. \tag{9}$$

This normalization achieves two objectives. First, by controlling for the effect of the overall level of variance, it makes the measure scale invariant, being bounded between -1 and 1. Absent such normalization, the asymmetry of a given currency may appear relatively high/low in the cross section just because the overall level of volatility is high/low (see, e.g., Bollerslev, Li, and Zhao, 2020, for an application of a similar realized measure in equities). Second, the normalized measure satisfies the properties that a skewness measure should have, such that it equals conditional skewness under some mild conditions (see, e.g., Feunou, Jahan-Parvar, and Tedongap, 2016).[14] For this reason, we refer to this normalized asymmetry measure as implied skewness.

Akin to the cubic contract of Bakshi et al. (2003), the above measure of risk-neutral skewness involves a long position in OTM calls and a short position in OTM puts. Thus, when the risk neutral distribution is left skewed, the combined cost of positioning in puts is larger than the combined cost of positioning in calls. That is, put options will be priced at a premium relative to calls. However, our measure and theirs differ in the weights that drive the combinations of contracts, as well as in the normalization adopted.

3.2. Objective ($\mathbb{P}$) Expected Measures

We then proceed to construct the objective counterparts to the risk-neutral measures in Eqs. (4), (6), (8), and (9). Specifically, the objective measures are defined as follows:

$$\widehat{RV}_{t,t+\tau} \equiv \mathbb{E}^{\mathbb{P}}_t\Big[RV_{t,t+\tau}\Big], \quad \widehat{RV}^{U}_{t,t+\tau} \equiv \mathbb{E}^{\mathbb{P}}_t\Big[RV^{U}_{t,t+\tau}\Big], \quad \widehat{RV}^{D}_{t,t+\tau} \equiv \mathbb{E}^{\mathbb{P}}_t\Big[RV^{D}_{t,t+\tau}\Big]. \tag{10}$$

As before, the objective expectation of variance asymmetry is given by

$$\widehat{RV}^{U/D}_{t,t+\tau} = \widehat{RV}^{U}_{t,t+\tau} - \widehat{RV}^{D}_{t,t+\tau}, \tag{11}$$

[14]For any unimodal random variable, X, with mode m, define $\Gamma(X) = (\sigma_u^2 - \sigma_d^2)/(\sigma^2)$, where $\sigma^2 \equiv Var(X)$ is its variance, and $\sigma_u^2 \equiv Var(X|X > m)$ and $\sigma_d^2 \equiv Var(X|X \leq m)$ are its upside and downside semivariances, respectively. Then, it holds that (i) if $Y = aX + b$ for any constants $a > 0$ and $-\infty < b < +\infty$, then $\Gamma(X) = \Gamma(Y)$; (ii) if X is symmetric, then $\Gamma(X) = 0$; and (iii) if $Y = -X$, then $\Gamma(Y) = -\Gamma(X)$. Thus, $\Gamma(X)$ meets the three conditions in Groeneveld and Meeden (1984) that a skewness measure should satisfy. Specifically, the normalization is key for $\Gamma(X)$ to meet the first skewness condition. Moreover, note that $\Gamma(X)$ cannot be a measure of kurtosis because $\Gamma(-X) = -\Gamma(X)$, and $\Gamma(X) = 0$ if X is symmetric.

which is further normalized by the total expected variance, resulting in an expected objective measure of skewness:

$$\widehat{RSK}_{t,t+\tau} \equiv \frac{\widehat{RV}^{U}_{t,t+\tau} - \widehat{RV}^{D}_{t,t+\tau}}{\widehat{RV}_{t,t+\tau}}. \tag{12}$$

3.3. Moment Risk-Premium Measures

A large body of the finance literature has studied the ability of model-free measures of the variance risk premium (VRP) to predict asset returns in different markets. Bollerslev, Tauchen, and Zhou (2009) show that the variance risk premium can be well approximated by the difference between the expected realized and option-implied variances. Thus, we measure the VRP as

$$\begin{aligned} VRP_t &= \mathbb{E}^{\mathbb{P}}_t\Big[RV_{t,t+\tau}\Big] - \mathbb{E}^{\mathbb{Q}}_t\Big[RV_{t,t+\tau}\Big] \\ &= \widehat{RV}_{t,t+\tau} - IV_{t,t+\tau}, \end{aligned} \tag{13}$$

where IV and $\widehat{RV}$ are defined in Sections 3.1 and 3.2, respectively. Della Corte, Ramadorai, and Sarno (2016) are among the first to construct this measure for currencies, showing that individual currency variance risk premia help predict the cross-section of currency returns.

Moreover, we decompose the variance risk premium into its upside and downside components as follows

$$VRP_t = \underbrace{\big(\widehat{RV}^{U}_{t,t+\tau} - IV^{U}_{t,t+\tau}\big)}_{VRPU_t} + \underbrace{\big(\widehat{RV}^{D}_{t,t+\tau} - IV^{D}_{t,t+\tau}\big)}_{VRPD_t}, \tag{14}$$

where $VRPU_t$ and $VRPD_t$ capture the upside and downside variance risk premia, respectively. Similar to Feunou, Jahan-Parvar, and Okou (2018), one can then easily recover the asymmetry risk premium as the spread between upside and downside VRPs:[15]

$$VRPUD_t = VRPU_t - VRPD_t. \tag{15}$$

Finally, we refer to the wedge between expected realized (objective) and option-implied (risk-neutral) skewness as the skewness risk premium,

$$SRP_t = \widehat{RSK}_{t,t+\tau} - ISK_{t,t+\tau}, \tag{16}$$

[15] Feunou, Jahan-Parvar, and Okou (2018) term this risk premium as the "signed jump" or "skewness" risk premium. We avoid calling it skewness risk premium as, without the normalization, the underlying measures do not fullfil entirely the conditions for a skewness measure set in Groeneveld and Meeden (1984). Therefore, we simply refer to it as the asymmetry risk premium.

which lies at the heart of our empirical analysis. To our knowledge, we are the first to use this measure of skewness risk premia for currencies. With comparison to standard measures of skewness risk premia that rely on the difference between realized and risk-neutral normalized central third moments (e.g., Fan, Xiao, and Zhou, 2022 for equities), this setup has the advantage that we do not need to compute the realized third moment, which is usually very sensitive to outliers and data frequency and hence can be very difficult to estimate in practice (see, e.g., Kim and White, 2004; Ghysels, Plazzi, and Valkanov, 2016; Bollerslev, 2021). We also do not need to compute the implied third moment, which is sensitive to the numerical methods used (see, e.g., Jiang and Tian, 2005; Huang and Li, 2019).[16]

4. Data and Currency Portfolios

Our data combine several sources, described below, and cover the period from January 1998 to December 2021 for a total of 28 currencies, expressed relative to the U.S. Dollar. The start of the sample and the size of the cross-section are largely dictated by the availability of liquid currency option data. In what follows, we first present the underlying data used to construct excess returns and option signals, and then turn to review the currency factors and portfolios.

4.1. Currency Options, Excess Returns, and Skewness Risk premia

`Currency Options.` We obtain currency options data from a major investment bank for the following 28 countries with respect to the U.S. dollar: Australia, Brazil, Canada, Switzerland, Czech Republic, Denmark, Euro, Hong Kong, Hungary, Indonesia, India, Israel, Japan, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Singapore, South Africa, South Korea, Sweden, Taiwan, Thailand, Turkey, and the United Kingdom. It is important to employ a relatively large cross-section of individual currencies including both safe and emerging currencies for examining skewness risk, which is inherently related to sovereign/default risk. More generally, there is a lot of value in analyzing portfolios constructed from a broad set of currencies outside the G10, as does much literature in this area of research, for at least two reasons. First, the trading

[16] Kozhan, Neuberger, and Schneider (2013) compute the skewness risk premium differently, by considering the expected excess return from holding a skewness swap, which captures the premium for being exposed to third-moment risk. More generally, all the risk premia defined above are computed as differences between objective and risk-neutral expectations, as is typically done in the literature. However, this implies that they are not profits from a trading strategy (e.g., Schneider and Trojani, 2018). Nevertheless, two observations are in order. First, the difference between the risk premium calculated using the standard spanning formulae of Bakshi, Kapadia, and Madan (2003) and its tradable counterpart is quantitatively small, as documented, e.g., in Feunou, Jahan-Parvar, and Okou (2018). Second, individual currency SRPs are not the final object of interest of our study, but rather the signals used to sort currencies and to construct cross-sectional trading strategies for currency returns. Therefore, in this paper we are not interested in the returns from trading skewness swaps.

volume associated with currencies outside the G10 is large both in absolute terms and relative to, say, small or even moderately large stocks used in the equity asset pricing literature, which makes it difficult to consider these currencies as minor assets to be excluded from the analysis.[17] Second, non-G10 currencies are known to enhance the risk-return profile (performance) of many currency strategies. For example, larger currency universes that include emerging markets substantially increase the Sharpe ratio for carry (e.g., Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a) and especially for momentum, which is known to perform poorly in the most liquid G10 currencies and to originate mainly from emerging markets (e.g., Menkhoff et al., 2012b). Understanding the risk-return profile in currency markets without using emerging market currencies in the analysis can therefore lead to an incomplete characterization of the currency SDF.

For a given maturity, the option data include Garman and Kohlhagen (1983) implied volatility quotes for five different combinations of plain-vanilla options: at-the-money (ATM) delta-neutral straddles, 10 delta and 25 delta risk-reversals, and 10 delta and 25 delta butterfly spreads. The ATM delta-neutral straddle combines a call option and a put option with the delta of 50 but with opposite sign such that the total delta is zero. This is the at-the-money implied volatility quoted in the over-the-counter FX market. In a risk reversal, the trader buys an OTM call and sells an OTM put with symmetric deltas, and the butterfly spread is constructed as the difference between the average implied volatility of an OTM call and an OTM put and the implied volatility of a straddle. From these data, we can recover the implied volatilities for call and put options with deltas of 10, 25, and 50. To convert deltas and implied volatilities into strike prices and option prices, we employ domestic and foreign interest rates, obtained from *Datastream*.

Based on considerations of both data availability and liquidity (trading volume), we work with three-month maturity currency options data in the paper. Using the available five implied volatility data points, we follow the interpolation and extrapolation methods of Jiang and Tian (2005) to construct the implied volatility surface and then compute the corresponding option values using the formulae of Garman and Kohlhagen (1983). The integrations in Section 3.1 are then solved numerically to obtain option-implied variance and semivariances; we provide a detailed description of the relevant numerical methods in the Internet Appendix (Section I).

`Spot and Forward Exchange Rates.` We obtain spot and one-month forward exchange rates with respect to the U.S. dollar (USD) for the above 28 currencies from Barclays Bank International (BBI) and WM/Reuters via *Datastream*. We take the perspective of a U.S. investor and define the exchange rate as units of USD per unit of foreign currency

[17] From the 2019 BIS Triennial Survey, for example, the average net daily total turnover in U.S. dollars for FX spot transactions was 48bn for the Mexican peso (MXZ) and 27bn for the South African rand (ZAR). From our calculations, based on the daily volumes and closing prices of traded shares, in 2019 the average daily traded volumes in U.S. dollars was about 7bn for Amazon and 6bn for Apple stocks.

(FCU), i.e. FCU/USD. As a result, an increase in the spot and forward rates correspond to an appreciation of the foreign currency. The empirical asset pricing analysis is carried out at the monthly frequency, whereby we compute excess returns by sampling end-of-month spot and forward rates. We construct monthly measures of realized variance and semivariances using the previous three-month daily spot exchange rate data.

`Currency Excess Returns.` The excess return on buying a foreign currency in the forward market at month t and then selling it in the spot market at month $t+1$ is given by

$$X_{i,t+1} = \frac{S_{i,t+1} - F_{i,t}}{S_{i,t}}, \tag{17}$$

where $S_{i,t}$ and $F_{i,t}$ are the currency i spot and forward rates at month t, respectively. The excess return can be decomposed into its spot-return and forward-premium components as follows

$$X_{i,t+1} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \frac{S_{i,t} - F_{i,t}}{S_{i,t}} \approx r_{i,t+1} + \big(i_{i,t} - i_t\big), \tag{18}$$

where $r_{i,t+1}$ is the spot exchange rate return, and $i_{i,t}$ and i_t are the foreign and U.S. dollar interest rates, respectively. The approximation is due to the fact that we follow the common practice to use forward rates rather than interest rate differentials to compute excess returns, so that $fp_{i,t} = \frac{S_{i,t}-F_{i,t}}{S_{i,t}} \approx i_{i,t} - i_t$ under covered interest rate parity (CIP).

Combining all data sources together, the sample spans the period from January 1998 to December 2021. However, the time periods differ across currencies, as the data for some currencies are not available since January 1998. Following the literature, for a given currency we remove observations that occur at times of large failures of CIP (see, e.g., Nucera, Sarno, and Zinna, 2024, and references therein). We provide the detailed list of currencies, indicating the sample period and CIP deviations for each currency, in the Internet Appendix (Table A1).

`Summary Statistics.` Table A2, in the Internet Appendix, presents summary statistics for the currency returns, skewness risk premia, and the risk-neutral and realized measures of variance and (upside and downside) semivariances. To compute realized measures, we demean returns as suggested by Bollerslev (2021).[18] Specifically, for a given window τ, we detract from the daily returns the average daily return between t and $t+\tau$, $k_{t,t+\tau} = \sum_{d=1/21}^{\tau}(r_{t+d})/(21 \times \tau)$. To obtain SRP, we proxy the inputs to $\widehat{RSK}$ with their lagged realized measures to ensure that it is bounded between -1 and 1, so that it fulfills the skewness properties and can be used together with ISK to construct skewness risk premia.

[18]Bollerslev (2021) notes that the finance literature often constructs monthly measures from daily returns (as we do), meaning that the impact of price drift may not be so immaterial, introducing a wedge between in-fill asymptotics and empirical measures. Therefore, to help alleviate such concerns, he suggests using mean-adjusted returns in the construction of upside and downside measures of semivariance. Moreover, Bollerslev, Li, Patton, and Quaedvlieg (2020) find that the use of daily data in the estimation of monthly semicovariances impacts on the estimates, but the main economic properties of the estimates remain intact.

This approach, which is the same as used by Bollerslev, Tauchen, and Zhou (2009) and Della Corte, Ramadorai, and Sarno (2016), makes $\widehat{RSK}$ directly observable at time t, and requires no modeling assumptions.

The table shows that the annualized currency returns (denoted CRet in the table) have, on average across currencies, a mean of about 1.3% and a standard deviation of about 10.5%; moreover, they are left-skewed with a skewness of about -0.37, and are clearly leptokurtic as the kurtosis is as large as 7.22.

We see that implied variance (IV) is mainly driven by the downside implied semivariance, while realized variance (RV) is roughly equally due to downside and upside realized semivariances. Moreover, it is apparent that IV is higher than RV. Similarly, implied and realized downside semivariances (IVD and RVD) are larger than their respective upside semivariances (IVU and RVU), although this is more evident for the implied measures, suggesting that the measures of the risk-neutral and realized skewness are both negative on average.

The skewness risk premium (SRP) is positive on average: it has a mean of about 0.17 and a standard deviation of 0.33, which means that the risk-neutral skewness is on average more negative than its realized counterpart. This suggests that investors are particularly averse to large depreciations in the foreign currency, which is in turn consistent with the notion that the U.S. Dollar tends to appreciate in bad times (see, e.g., Maggiori, 2017; Jiang et al., 2021). The skewness risk premium is left-skewed with a skewness of -0.33, and its kurtosis is slightly larger than 3.

4.2. SRP Portfolios and Factors

In what follows, we present the SRP portfolios and construct a tradable and a nontradable SRP factor. We then turn to listing the portfolios and factors associated with 11 other investment strategies which, together with the SRP portfolios, represent the set of test assets.

`SRP Portfolios.` At the end of each month, we sort currencies into five portfolios on the basis of individual SRPs. We assign 20% of all currencies with the lowest SRPs to Portfolio 1 (P1) and 20% of all currencies with the highest SRPs to Portfolio 5 (P5). We then form a long-short portfolio that buys P5 and sells P1. We hold those portfolios till the next month and compute their realized equal-weighted mean excess currency returns.

Panel A of Table 1 presents the summary statistics of SRP-based portfolios. First, we see that there is a tendency of portfolio returns to increase from P1 to P5, though this tendency is not monotonic. Second, more importantly, the long-short portfolio (SRP_{HML}) earns a highly statistically significant and economically large mean excess return: the annualized monthly average excess return is about 5.47% with a t-statistic of 3.31, and its annualized Sharpe ratio is 0.75. The long-short portfolio returns are left-skewed and

Table 1: SRP Portfolios

The table presents the performance of the portfolios constructed by sorting currencies first on their currency skewness risk premia (SRP), and then on the objective ($\mathbb{P}$) and risk-neutral ($\mathbb{Q}$) components of the SRPs. To begin with, at the end of each month, we allocate currencies to five portfolios using as signals (or sorting variable) their individual SRPs. Specifically, we allocate 20% of currencies with the lowest SRPs to Portfolio 1 (P1) and 20% of currencies with the highest SRPs to Portfolio 5 (P5). As we move from P1 to P5, the portfolios include currencies with increasing SRPs. We then form a spread portfolio (HML) that longs P5 and shorts P1. We hold these portfolios to the next month and compute their realized mean excess returns. Panel A presents summary statistics of the SRP portfolio excess returns, while Panel B reports the statistics for the currency (r) and interest rate (fd) components of the currency excess returns. In Panel C, we present the excess returns of the portfolios constructed using either the $\mathbb{P}$ or the $\mathbb{Q}$ legs of the SRPs as sorting variables. The Newey-West t-statistics are presented in brackets. The sample period is from February 1998 to December 2021, at a monthly frequency.

	Panel A: SRP Portfolios					
	P1	P2	P3	P4	P5	HML
Mean	-0.62	1.32	1.05	0.68	4.85	5.47
	(-0.53)	(0.77)	(0.59)	(0.36)	(2.47)	(3.31)
STD	5.61	7.83	8.39	8.50	8.78	7.30
SR	0.11	0.17	0.13	0.08	0.55	0.75
Skew	0.34	-0.13	-0.49	-0.44	-0.72	-0.70
Kurt	4.60	3.89	4.87	4.25	5.23	5.79
AC	-0.03	0.08	0.07	0.08	0.11	0.14
	Panel B: SRP Portfolio Components					
	P1	P2	P3	P4	P5	HML
r	0.54	1.51	0.25	-1.81	-2.05	-2.59
	(0.46)	(0.89)	(0.14)	(-0.96)	(-1.08)	(-1.70)
fd	-1.16	-0.19	0.80	2.49	6.90	8.06
	(-8.38)	(-1.56)	(5.05)	(13.2)	(15.6)	(16.5)
	Panel C: $\mathbb{P}$ and $\mathbb{Q}$ Skewness Portfolios					
	P1	P2	P3	P4	P5	HML
$\mathbb{P}$ Leg	2.20	0.91	1.23	1.20	1.63	-0.57
	(1.30)	(0.51)	(0.69)	(0.75)	(1.07)	(-0.47)
$\mathbb{Q}$ Leg	3.22	1.99	1.95	-0.07	-0.21	-3.43
	(1.58)	(0.99)	(1.11)	(-0.04)	(-0.17)	(-1.86)

leptokurtic, and they are not highly autocorrelated. Third, we find that the SRP long-short portfolio return mainly stems from the long portfolio (P5), whose annualized mean excess return is about 4.85% ($t = 2.47$) and whose annualized Sharpe ratio is about 0.55; the short portfolio (P1) displays an annualized mean excess return of about -0.62%, which is not statistically significant, with a very small annualized Sharpe ratio.

We decompose currency portfolio excess returns ($\approx r + fd$) into their respective spot exchange rate returns (r) and interest rate differentials, or forward discounts (fd) as in Eq. (18). The results, presented in Panel B of Table 1, suggest that the spot returns of the quintile portfolios do not have clear increasing or decreasing tendency and that the mean excess return of the long-short portfolio is not statistically significant; however, the interest rate differentials of the quintile portfolios have a monotonically increasing pattern, with the long-short portfolio showing a positive and highly statistically significant average return. Thus, these results indicate that the positive predictive relationship between individual currency skewness risk premia and future currency excess returns in Panel A stems mainly from the positive relationship between currency skewness premia and interest rate differentials. This evidence is consistent with the rare disaster model of Farhi and Gabaix (2016), and with the properties of the carry strategy excess returns (which are also primarily driven by the interest rate differentials rather than by the spot returns).

We further examine the performance of the portfolios constructed using the expected objective and risk-neutral skewness, i.e. the two legs of SRP, as distinct sorting variables. Panel C of Table 1 presents quintile portfolios and the long-short portfolio based on each of the $\mathbb{P}$ and $\mathbb{Q}$ legs of SRP. We see that the quintile portfolio returns based on the $\mathbb{P}$ leg tend to decrease from P1 to P5; however, its long-short portfolio mean excess return is very small and not statistically significant. We further notice that, even though the quintile portfolio returns based on the $\mathbb{Q}$ leg monotonically decrease from P1 to P5, the long-short portfolio mean excess return is only marginally statistically significant and is much smaller (in absolute value) than that based on SRP. These results suggest that the large average excess return and Sharpe ratio generated by the long-short strategy that sorts on SRP cannot be attributed to or replicated by either the $\mathbb{Q}$ or $\mathbb{P}$ estimates of skewness, as they are driven by skewness risk premia that require both $\mathbb{Q}$ and $\mathbb{P}$ estimates. Hence, a natural interpretation of the positive mean excess return of the SRP-based long-short portfolio is that investors dislike uncertainty related to skewness risk, resulting in a positive relationship between skewness risk premia and future currency excess returns.[19]

It is desirable to investigate how the SRP trading strategy behaves as we slice the currency cross-section. We have argued that it is important to use a broad cross-section of currencies, including not only developed but also emerging market currencies, to examine skewness risk in currency markets. Here, we inspect how the strategy performs when we implement the same portfolio sorts separately on G10 currencies (i.e., AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD, SEK) and on the residual 18 emerging currencies.

[19] We implement two additional empirical exercises. First, to address possible concerns about the extrapolation method, we also construct risk-neutral measures using narrower moneyness bounds when solving integrals. We find that the resulting SRP portfolios are quantitatively and qualitatively the same. Second, we sort currencies into portfolios by replacing our measure of SRP based on semivariances with the standard measure of SRP resting on the normalized central third moment (e.g., Fan, Xiao, and Zhou, 2022). Specifically, we construct objective skewness at the end of each month by computing the normalized central third moment using the previous three-month daily spot returns and risk-neutral skewness based on the cubic contract as in Bakshi, Kapadia, and Madan (2003); their difference defines the standard skewness risk premium. We find that, using this alternative measure of SRP to sort currencies into portfolios, the resulting trading strategy is no longer profitable; essentially, all results of Table 1 vanish. This evidence lends support to the arguments mentioned earlier that the measure of SRP constructed from semivariances are more robust than those relying on the central third moment and hence can have different empirical properties.

Table A3, in the Internet Appendix, shows that SRP_{HML} earns an annualized mean return of only 2.31%, which is not statistically significant, when restricting the sample to G10 currencies. By contrast, using only emerging market currencies, the SRP strategy earns an annualized mean return of 6.42%, which is highly statistically significant ($t = 3.26$). This finding is not surprising for two main reasons. First, non-G10 currencies are known to enhance the risk profile of many popular currency trading strategies. Second, it is reasonable that crash/skewness risk is a particularly relevant source of risk for emerging market currencies, which are notoriously more prone to sudden stops in capital flows and speculative attacks.[20] Taken together, the results point to the value of having a currency universe that comprises both developed and emerging markets.

`SRP Factors.` So far, the analysis demonstrates the existence of a highly profitable currency investment strategy, built by sorting currencies on their individual skewness risk premia. We have argued that these high average returns constitute compensation for skewness risk. It is therefore natural to ask if skewness risk premia constitute a systematic source of risk in currency returns. Put simply, is there a risk-return trade-off in currency returns determined by currencies' skewness risk premia? To address this question, we run asset pricing tests using an SRP candidate pricing factor. We opt to construct both a tradable and a nontradable SRP factor, for reasons explained below.

`Tradable Factor.` A natural candidate for a tradable factor is the high-minus-low SRP portfolio, SRP_{HML}, of Table 1 (Panel A). To inspect its evolution, the top panel of Figure 2 presents its time series (shaded areas show NBER recession periods). Notably, the strategy tends to perform poorly during market downturns. For example, its return turns strongly negative during the GFC and the more recent Covid-19 pandemic. This evidence is suggestive of a risk-return explanation: the SRP strategy seems to offer poor protection to investors in bad times. Hence, the overall high average return would be compensation for the inherent riskiness of the strategy.[21]

`Nontradable Factor.` We also construct a nontradable SRP factor, using a measure of the dispersion in individual currency SRPs. Specifically, at each time t, we compute the cross-sectional standard deviation of the currency SRP signals, and in doing so obtain a time series of SRP standard deviations. We then take their AR(1) innovations as our SRP nontradable factor, SRP_{NT}.[22] We plot the SRP nontradable factor in the lower panel

[20]However, note that although the G10 SRP risk premium is not statistically significant over the full sample, it is significant prior to the financial crisis (Figure A1).

[21]We construct the tradable factor as HML, but we have also verified that the linear and rank SRP tradable factors (based on strategies that trade all currencies rather than just those in the corner portfolios) are also highly profitable. In fact, we find that their risk premia are roughly 2% and 3.5% (both statistically significant at the 1% level), the Sharpe ratios are 0.62 and 0.64, and their returns have skewness of -0.96 and -0.76, respectively. This suggests that the SRP tradable factor is robust to the construction scheme employed. Moreover, this evidence suggests that the HML factor is not driven by outliers, as linear and rank strategies trade the full set of currencies in each month, unlike the HML strategy which trades only the top and bottom five currencies.

[22]This way of constructing a nontradable factor from characteristics is not novel, and closely relates

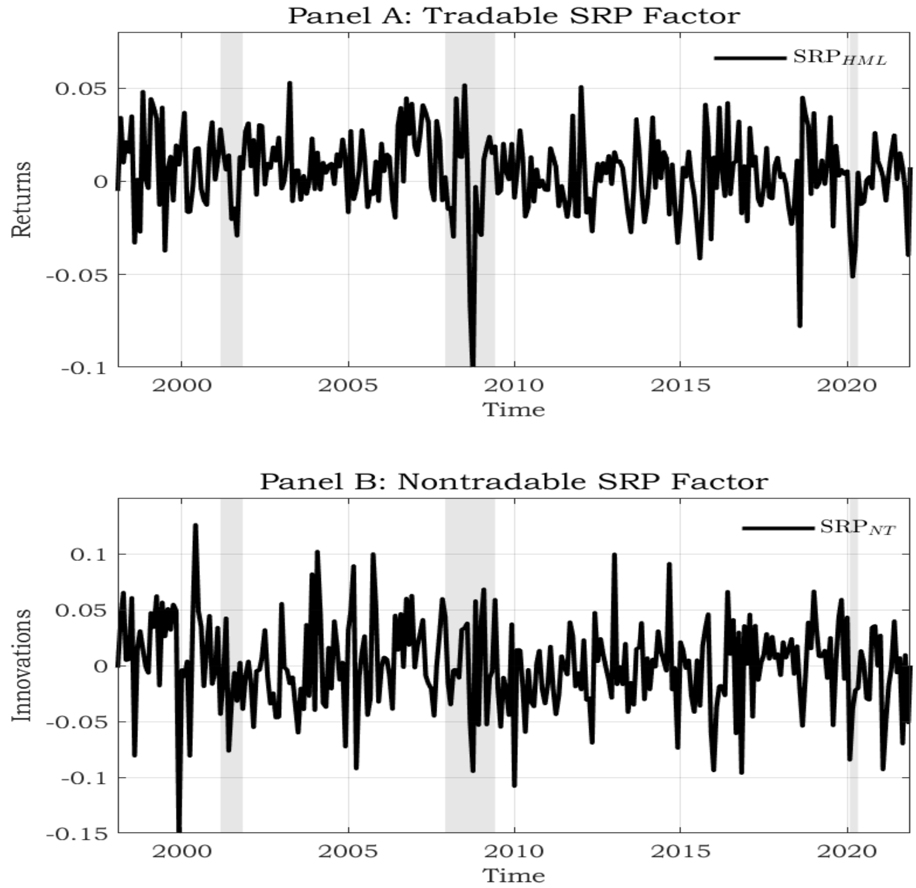

Figure 2: Tradable and Nontradable SRP Factors

The figure shows the time series of the SRP factors. Panel A presents the tradable HML SRP factor (SRP_{HML}), i.e., the long-short trading strategy, which buys the top quintile portfolio of currencies with high SRPs and shorts the bottom quintile portfolio of currencies with low SRPs. Panel B shows the nontradable SRP factor (SRP_{NT}), i.e., the innovation to the time series of cross-sectional standard deviations of the monthly currency SRP signals. The sample period is from February 1998 to December 2021 at monthly frequency.

of Figure 2. Similar to SRP_{HML}, SRP_{NT} also tends to drop during market downturns, reaching extremely negative values. The correlation between SRP_{HML} and SRP_{NT} is about 0.33. Thus, the spread in factor characteristics tends to widen when the factor's excess return is large.

While nontradable factors tend to perform less well in asset pricing tests than tradable factors (e.g., Gospodinov, Kan, and Robotti, 2019), SRP_{NT} likely captures skewness risk (premia) more directly than its tradable counterpart, SRP_{HML}. This is because, by

to the spread in factor characteristics between long and short positions. This type of spread has been shown to be a valuable conditioning variable for expected returns in the context of other markets and strategies/signals (Ilmanen et al., 2021). For example, Koijen et al. (2018) show that carry is a simple observable characteristic that is a component of the expected returns on an asset. For this reason, it can provide information to predict expected returns.

construction, SRP_{HML} combines skewness risk premia (sorting variable) with currency excess returns (sorted variable). But excess returns are not neutral to sources of risks other than crash/skewness (in the sense of, e.g., Jurek, 2014). Thus, one may argue that SRP_{HML} does not provide a pure measure of the premium that investors are willing to pay to hedge their currency exposures to variation in skewness. However, despite the evident appeal of working with nontradable factors, the estimation of their risk premia is notoriously cumbersome: these factors often contain substantial measurement error, and a model-free estimate of the risk premium is not readily available. Therefore, there are both pros and cons in using tradable or nontradable factors, and we perform the asset pricing analysis using both types of factors.

`Pricing SRP portfolios.` As is standard in the literature, when a novel tradable strategy is proposed, the first step consists of pricing the cross-section of the strategy portfolios. Due to the small number of test assets, however, one is constrained to use parsimonious SDFs. A natural choice is to use two-factor SDFs, including the Dollar factor to pin down the level of the SDF, and the strategy HML factor to capture the spread in returns (see, e.g., Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012b; Menkhoff et al., 2017). Therefore, we consider a parsimonious two-factor SDF including the Dollar factor and the SRP factor (either SRP_{HML} or SRP_{NT}), so that the time-t SDF (m_t) is given by

$$m_t = 1 - b_{DOL}\big(DOL_t - \mu_{DOL}\big) - b_{SRP}\big(SRP_t - \mu_{SRP}\big). \tag{19}$$

We perform this cross-sectional analysis in Table 2, using the conventional two-pass Fama-MacBeth (FMB) and GMM estimators (see the Internet Appendix, Section IV, for a detailed description of the estimators).

In Panel A, the SDF features the DOL and SRP tradable factors, i.e. $SRP_t = SRP_{HML}$ in the SDF. The test assets consist of the five SRP portfolios. Following Lewellen et al. (2010), we also add the SRP_{HML} factor to the cross-section so that the factor risk-premium estimate should be closer to its sample average return (this is important as no-arbitrage implies that the two should be equal). Consistently, we find that the two-pass risk-premium estimate of SRP_{HML} is 5.47%, the same as its sample mean and highly statistically significant, with a t-statistic above 3 (Panel A.I). The cross-sectional adjusted R^2 is 94%, and the p-value of the χ^2 test is 0.55, so that we cannot reject the null that the pricing errors – the *alpha*s in the second pass – are statistically jointly equal to zero.

The statistically significant risk-premium estimate does not necessarily imply, however, that the corresponding factor is a *true* SDF factor (e.g., Cochrane, 2005; Burnside, 2011). In Panel A.II, we therefore use GMM to directly estimate the SDF-weights, i.e. the loadings b in the SDF, as well as the risk premia by the first-stage GMM. We find that the estimate of b_{SRP} is about 0.01 and is highly statistically significant, with a t-statistic

Table 2: Pricing SRP Portfolios

The table presents the results of the cross-sectional asset pricing tests using the SRP portfolios as test assets. In Panel A, the SDF consists of the Dollar factor, DOL, and the tradable SRP factor, SRP_{HML}, and in Panel B, it includes the Dollar factor and the nontradable SRP factor, SRP_{NT}. The test assets are the five SRP portfolios, plus the SRP_{HML} factor. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage of the generalized method of moment (GMM) estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021.

	A. Tradable SRP Factor				B. Nontradable SRP Factor		
	A.I FMB				B.I FMB		
	DOL	SRP_{HML}	χ^2		DOL	SRP_{NT}	χ^2
λ	1.407	5.473	3.07	λ	1.377	2.604	1.83
(NW)	(0.98)	(3.34)	[0.55]	(NW)	(0.96)	(2.68)	[0.77]
(Sh)	(0.98)	(3.66)		(Sh)	(0.98)	(3.07)	
	RMSE	Adj. R^2			RMSE	Adj. R^2	
	0.51	0.94			0.45	0.95	
	A.II GMM				B.II GMM		
	DOL	SRP_{HML}	χ^2		DOL	SRP_{NT}	χ^2
b	-0.002	0.009	3.07	b	0.000	0.166	1.85
	(-0.56)	(3.12)	[0.55]		(0.08)	(2.88)	[0.76]
λ	1.406	5.473		λ	1.377	2.604	
	(0.99)	(3.71)			(0.96)	(2.86)	

of 3.12, whereas the estimate of b_{DOL} is not statistically significantly different from zero. The χ^2 test confirms that the pricing errors are jointly equal to zero.

In Panel B, we evaluate the performance of the nontradable factor in pricing the cross-section of SRP portfolios, by setting $SRP_t = SRP_{NT}$ in the SDF. Using the two-pass method, the estimate of the annualized risk premium of SRP_{NT} is about 2.60% and is highly statistically significant (Panel B.I).[23] The cross-sectional adjusted R^2 is 95%, and the χ^2 test suggests that we also cannot reject the null that the pricing errors are jointly equal to zero. Furthermore, the GMM estimate of $b_{SRP_{NT}}$ is about 0.17 and is very precisely estimated, with a t-statistic about 2.88. In line with the FMB evidence, the χ^2 test cannot reject the null that the alphas are jointly zero.

This evidence clearly shows that the SRP factors, either tradable or nontradable, price

[23]The model-implied estimate of the SRP_{HML} premium is about 5.50% (not reported), being very close to the factor sample average. We also evaluate the performance of SRP_{NT} (i.e., using a two-factor SDF with DOL and SRP_{NT}) in pricing the cross-section of CAR quintile and HML portfolios and find that the model-implied risk premium of the CAR HML factor is about 5.72%, which is very close to its sample average.

the SRP portfolios. In what follows, we center the baseline asset pricing analysis mainly around the tradable factor, but we carry out analysis using the nontradable factor in parallel, reported in the Internet Appendix.

4.3. Test Assets and Competing Factors

In this subsection, we present the test assets (and the associated factors), which include portfolio returns resulting from a combination of novel and more conventional currency investment strategies. Among the latter strategies, we consider carry (e.g., Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a; Lettau, Maggiori, and Weber, 2014; Koijen et al., 2018), short-, medium-, and long-term currency momentum (e.g., Menkhoff et al., 2012b, Asness, Moskowitz, and Pedersen, 2013), currency value (e.g., Asness, Moskowitz, and Pedersen, 2013; Kroencke, Schindler, and Schrimpf, 2014; Menkhoff et al., 2017), global imbalances based on net foreign assets (Della Corte, Riddiough, and Sarno, 2016), risk reversal (Della Corte, Ramadorai, and Sarno, 2016; Della Corte et al., 2022), and the volatility risk premium currency strategy (Della Corte, Ramadorai, and Sarno, 2016). We label these strategies as CAR, MOMS, MOMM, MOML, VAL, NFA, RR and VRP, respectively. We add three novel option-based strategies, which sort on the VRPD, VRPU, and VRPUD signals (see Section 3).[24] Therefore, in total we consider 11 currency investment strategies, in addition to the SRP strategy from which we obtain the SRP$_{HML}$ tradable factor.

`Portfolios Construction.` We provide a detailed description of each investment strategy in the Internet Appendix (Section III). Here we note that these strategies differ in the signals used to allocate currencies into portfolios (e.g., interest-rate differentials, past returns, etc.), but the sorting schemes are the same as that employed for SRP portfolios. All strategies are tradable in real time and rest on single sorts, whereby a single trading signal is used to sort currencies into five portfolios. As we move from P1 to P5, the portfolios contain currencies of increasing risk. Hence, if the risk-return trade-off holds, the high-minus-low spread portfolio (HML) should give a positive return because P5 contains currencies with high risk, whereas P1 includes currencies with low risk. Finally, we note that we work with a matched panel of signals: for a given currency and month, if the SRP signal is not available, we exclude the signals of the other strategies.

`Portfolios Performance.` Table A4 reports summary statistics of the portfolios associated with the 11 investment strategies. We find that except RR, VRP, and MOML,

[24]To construct the VRP, VRPD, VRPU, and VRPUD risk-premium signals, we employ ARX(1) forecasting regressions to obtain objective expected measures. Using notation local to this footnote and for a generic currency i, we recursively estimate $RV_{i,t+1-\tau,t+1} = \alpha_i + \beta_i RV_{t-\tau,t} + \gamma_i IV_{i,t,t+\tau} + \epsilon_{i,t+1}$, thus including both realized and risk-neutral variances as predictors. Specifically, we recur to random walk models to obtain forecasts for the first 12 months and implement forecasting based on ARX(1) using an expanding window since then. The same procedure is applied to predict the semivariances. We find that alternative prediction models provide qualitatively similar results, possibly due to the persistence in volatility.

these long-short strategies earn large and statistically significant mean excess returns at least at the 10% significance level. Overall, among these strategies, CAR singles out as the most profitable strategy, and its Sharpe ratio (0.72) is much higher than those of VRPU and VRPUD (0.52 and 0.47), which are the second and third most profitable strategies, respectively. This suggests that CAR remains one of the most profitable currency investment strategy (see, e.g., Lustig, Roussanov, and Verdelhan, 2011).[25] Nevertheless, in our sample SRP has an even higher Sharpe ratio than any of the 11 strategies considered (see Tables 1 and A4). The superior performance of CAR and SRP factors is clearly evident from visually inspecting the evolution over time of their respective cumulative excess returns (Figure 3, Panel A).

In light of the focus of the study, it is useful to look at the skewness of the HML portfolios (numbers in squared brackets in Table A4). Not surprisingly CAR and RR strategies have negatively skewed returns, but it is also evident that many other currency strategies present negatively skewed returns. NFA stands out as it displays the most negatively skewed returns, consistent with the hedging channel of Liao and Zhang (2024), and with the notion that skewness in the economy translates to skewness in asset returns. Strategies that rely on signals from options also show excess returns that are strongly negatively skewed, with VRPD and VRPU being the most and the least skewed ones, respectively. In contrast, strategies based on past-return signals have excess returns that are either positively skewed (especially MOMS) or with modest skewness (MOMM, MOML and VAL).

We then zoom into the top constituents of the corner portfolios in terms of frequency of appearance (Table A5, in the Internet Appendix). We find that the top-3 currencies that feature most often in SRP P1 are two safe funding currencies, JPY and CHF (89% ad 69%), and HKD (73%). In contrast, in P5 there are some of the high-yield currencies, and there seems to be more turnover in the portfolio constituents. The corner portfolio constituents of SRP and CAR are more similar than those of SRP and VRP, which are remarkably different. Momentum strategies single out as they display the highest turnover in the constituents of the corner portfolios.

Table A6 in the Internet Appendix reports cross-correlations for the excess returns of the 12 HML factors. Focusing on the SRP factor, we note that it displays especially high correlations with other option-based risk-premium factors (especially VRPD, VRPUD and VRPU) as well as CAR and RR, and sizable correlations with VRP, NFA and VAL. However, the correlation between the SRP factor and the momentum factors is close to zero, and indeed negative in the case of MOMS, suggesting that the source of

[25] While Della Corte, Ramadorai, and Sarno (2016) show that currency volatility risk premia have strong predictive power for currency returns using a sample ending in December 2013, we find that its performance becomes much weaker when extending the sample to December 2021. Consistent with Menkhoff et al. (2012b) and Asness, Moskowitz, and Pedersen (2013), the results show that momentum strategies, especially short-term ones, perform fairly well.

predictability in momentum strategies is of different nature.

Finally, we turn to inspect the efficient portfolio frontiers (Figure 3, Panel B). To isolate the impact of CAR, SRP, and option-based risk-premium information, we consider three frontiers that are constructed using: 12 HML factors and the Dollar factor (i.e., all factors); all factors excluding the SRP factor; and all factors excluding the option-based risk-premium factors (SRP, VRP, VRPD, VRPU and VRPUD). We focus on SRP and the full set of option-based strategies since it is novel to use this broad menu of option-based strategies in currency asset pricing and little is known about their marginal contribution to performance in currency asset allocation. The resulting evidence is clearcut. The efficient frontier moves southeast when excluding SRP, and shifts dramatically southeast when excluding all option-based risk-premium strategies. This evidence is reflected in Sharpe ratios of the tangency portfolios on those three frontiers: their annualized Sharpe ratios are 1.15 (all), 1.08 (excluding SRP), and 0.97 (excluding all option-based risk-premium factors), respectively. It also shows that the information in SRP is not entirely subsumed by the other option-based risk-premium strategies.

In sum, this analysis shows that SRP signals are strong predictors of the cross-section of currency excess returns, and the SRP strategy yields the highest Sharpe ratio among the broad set of currency investment strategies considered. The currency frontier improves when investors can invest also in the SRP strategy. Moreover, the full set of option-based risk-premium strategies yields substantial improvements in the currency frontier. At the same time, many of the strategies considered have negatively skewed returns. However, MOMS is an exception in that it has positive skewed returns, so that it is likely to be disconnected or only weakly associated with SRP.

5. Optimal SDF, Risk Premia, and Asset Pricing Tests

So far we have performed the asset pricing tests using a small cross-section consisting of the SRP sorted portfolios. In doing so, the SRP factor risk-premium estimates are likely to be more efficient. The factor is likely to be strong in this small cross-section, which is by construction particularly informative about the HML factor, so that the first-pass exposures are more precisely estimated (e.g., see discussion in Giglio et al., 2024). However, we also know that the use of a small cross-section of test assets, which have a strong factor structure, may not provide a robust/valid test of an asset pricing model (Lewellen, Nagel, and Shanken, 2010). Therefore, it is necessary to implement cross-sectional asset pricing tests using a larger cross-section of test assets, and specifically with all test assets at our disposal ($N = 60$). To the best of our knowledge, this is the broadest cross-section of currency portfolio returns analyzed in the literature, which poses a challenge of dimensionality and raises the bar substantially in terms of recovering a parsimonious SDF that can price all asset returns.

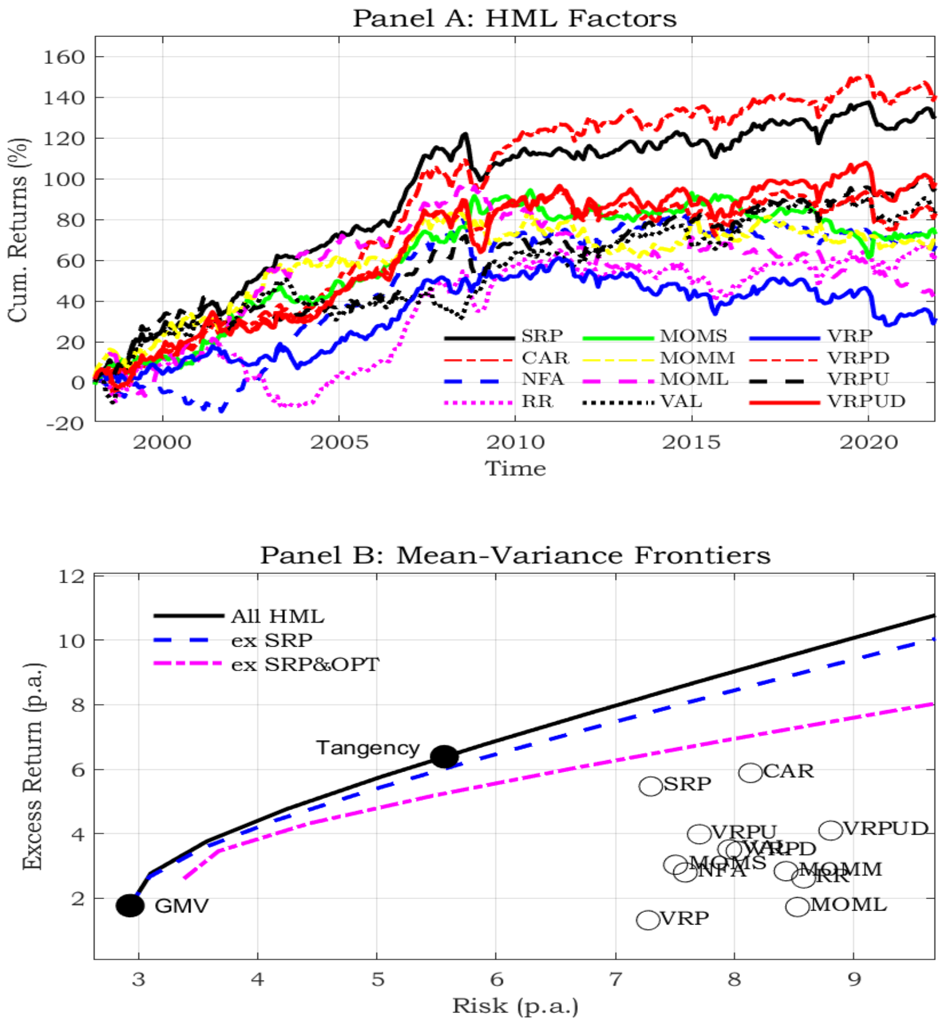

Figure 3: Factor Returns and Mean-Variance Frontiers

This figure shows, in Panel A, the cumulative sum of the monthly excess returns of the 12 HML factors (the 11 competing factors and the SRP factor) for the period from February 1998 to December 2021. In Panel B, it presents three mean-variance portfolio frontiers constructed using the full cross-section of the 12 HML factors (plus the Dollar factor) and some smaller cross-sections. Specifically, we consider cross-sections consisting of: (i) all factors (All HML); (ii) all factors except the SRP factor (ex SRP); (iii) all factors except the SRP and option-based risk-premium factors (i.e., VRP, VRPU, VRPD, VRPUD; ex SRP&OPT). GMV and Tangency represent the global minimum-variance portfolio and the tangency portfolio, respectively, from all factors. We also report the annualized excess return (sample mean) and risk (sample standard deviation) of each of the 12 HML factors. The sample period is from February 1998 to December 2021 at monthly frequency.

However, we are also acutely aware of the problems induced by omitted variables bias and measurement errors in standard asset pricing procedures. Therefore, we recur to the RP-PCA three-pass estimator, which combines the three-pass estimator developed by Giglio and Xiu (2021), GX hereafter, with the RP-PCA estimator of Lettau and Pelger (2020), LP hereafter. The RP-PCA method allows us to efficiently recover the latent-factor SDF from the panel of currency portfolios (test assets), ensuring that all portfolio returns are priced and no alpha is left unexplained. In turn, the resulting latent-factor SDF is a key input to achieve robust estimates of candidate factors' risk premia via the three-pass method. A detailed review of the RP-PCA and three-pass estimators is provided in the Internet Appendix (Section IV.2).

In what follows, we present the optimal latent-factor SDF extracted via RP-PCA and the three-pass risk premium estimates of the candidate factors (the slope factors of the 12 investment strategies) using this optimal SDF. We then conduct the conventional FMB and GMM asset pricing tests using a three-factor SDF including de-noised SRP and MOMS factors, in addition to the level Dollar factor. We show that even this parsimonious SDF prices the cross-section of test assets, i.e., the 60 currency portfolios associated with the 12 investment strategies, very accurately.

5.1. Three-Pass Inference

We perform the three-pass analysis using the full cross-section consisting of the 60 portfolio returns constructed based on the 12 sorting variables ($12 \times 5 = 60$). We establish the optimal-latent factor SDF, we then estimate both risk exposures and risk premia of all tradable factors, and recover de-noised versions of these factors.[26]

`Latent-Factor SDF.` Table 3 presents the statistics of the first nine extracted latent factors and the economic diagnostics of the associated currency SDF. We base the three-pass empirical analysis on rotated, orthogonalized latent factors with positive means. Following Nucera et al. (2024), we set $\omega = 20$ as the baseline RP-weight, which seems to be a reasonable choice also in our sample.[27]

By inspecting Table 3, the following observations are in order. First, as usual, the first factor (F_1) behaves as a strong factor, being relevant for a large set of portfolios, and hence cannot be omitted from the currency SDF (e.g., Lewellen, 2022). Its estimated mean (risk premium) is statistically insignificantly different from zero, which suggests that F_1 is essentially a systematic, level factor that captures mainly time series variation in the test assets.[28] Second, factors F_2 to F_7 clearly stand out as pricing factors. They all have high and precisely estimated means (risk premia), and their inclusion leads to a large improvement in the model pricing performance and cross-sectional fit: the seven-factor model achieves an R^2 above 99%, and the maximal Sharpe ratio (mSR) of the tangency portfolio spanned by these seven factors is 1.5 (annualized).[29] Third, the role of factors

[26]In what follows, we center the baseline asset pricing analysis mainly around the tradable factor, but we carry out analysis using the nontradable factor in parallel, reported in the Internet Appendix.

[27]We present in the Internet Appendix, Table A7, sensitivity analysis with different RP-weights, where we consider the case of PCA ($\omega = -1$) and RP-PCA with a lower and higher RP-weight ($\omega = 10$ and 50) than the baseline.

[28]All portfolios, or test assets, are positively exposed to F_1. Nucera et al. (2024) show that F_1 relates to the Dollar factor, whose risk premium can turn out to be marginally statistically significant depending on the sample considered. Nevertheless, its role in the SDF is mainly that of a strong level factor.

[29]In Figures A2 and A3 we present test assets' risk exposures and explained variations by latent

Table 3: Latent-Factor Statistics and SDF Diagnostics

The table presents latent factor statistics and SDF diagnostics, obtained by implementing the first two steps of the RP-PCA three-pass estimator with baseline RP-weight (i.e., $\omega = 20$). We apply the estimator to the sample of $N = 60$ test assets consisting of the portfolios associated with the 11 currency investment strategies and the SRP strategy. We consider SDFs, $\varphi(F_{1-k})$, including an increasing number of latent factors, $k = 1, 2, \ldots, 9$. In *A.I Factor Statistics*, *I.a: Factors*, we report the statistics of the orthogonalized factors: the k-th factor's annualized mean ($\mu_{F,k}$); the k-th factor's annualized Sharpe ratio ($SR_{F,k}$); and the k-th factor's weight in the SDF, $\varphi_t = 1 - (\hat{F}_t - \mu_F)\hat{b}_{MV}^{\top}$ ($\hat{b}_{MV,k}$). In *A.II: SDF Diagnostics*, we present the SDF diagnostics. Specifically, *II.a: 1P* shows the first-pass diagnostics: the average idiosyncratic variance, $\overline{\sigma}^2_{\epsilon} = \frac{1}{N}\sum_{n=1}^{N}[Var(\hat{\epsilon}_n)/Var(X_n)]$; and the average root-mean-square pricing errors, $\overline{RMS}_{\alpha} = \sqrt{\hat{\alpha}\hat{\alpha}^{\top}/N}$, obtained by estimating $X_{n,t} = \alpha_n + \hat{F}_t\psi_n^{\top} + \epsilon_{n,t}$, for $n = 1..., N$ test assets, and $t = 1..., T$ months. *II.b: 2P* presents the second-pass diagnostics: the mean absolute errors (MAE) of the cross-sectional regression, $\overline{X}_n = \hat{\psi}_n\gamma^{\top} + a_n$, for $n = 1, \ldots, N$, where γ is the $1 \times k$ vector of latent factors' prices of risk; and the R-squared values ($R^2(\%)$). Finally, *II.c: mSR* reports the annualized maximal Sharpe ratio (SR) from the tangency portfolio of the mean-variance frontier spanned by the linear combination of the k selected latent factors, $\hat{F} \times \hat{b}_{MV}^{\top}$, where $\hat{b}_{MV}$ is a 1 × k vector with entries $\hat{b}_{MV,k} = \mu_{F,k}/\sigma^2_{F,k}$, with $\mu_{F,k}$ and $\sigma^2_{F,k}$ denoting the k-th factor's mean and variance; ΔSR denotes the difference in SRs between SDFs with k and $k-1$ factors. The sample period is from February 1998 to December 2021, at monthly frequency.

	A.I: Factor Statistics				A.II: SDF Diagnostics					
	I.a: Factors				II.a: 1P		II.b: 2P		II.c: mSR	
	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\overline{\sigma}^2_{\epsilon}$	$\overline{RMS}_{\alpha}$	MAE	$R^2(\%)$	SR	ΔSR
F_1	12.93	0.24	0.04	$\varphi(F_1)$	20.86	1.17	0.87	68.49	0.24	
F_2	7.89***	0.60	0.38	$\varphi(F_{1-2})$	15.79	0.92	0.44	83.95	0.64	0.41
F_3	5.66***	0.65	0.63	$\varphi(F_{1-3})$	13.61	0.79	0.26	94.21	0.91	0.27
F_4	4.67***	0.71	0.89	$\varphi(F_{1-4})$	12.37	0.70	0.17	98.03	1.16	0.24
F_5	3.75***	0.60	0.81	$\varphi(F_{1-5})$	11.33	0.60	0.12	98.72	1.31	0.15
F_6	3.00**	0.53	0.77	$\varphi(F_{1-6})$	10.46	0.51	0.09	99.26	1.41	0.10
F_7	2.70**	0.53	0.88	$\varphi(F_{1-7})$	9.77	0.42	0.07	99.61	1.50	0.10
F_8	0.71	0.14	0.23	$\varphi(F_{1-8})$	9.11	0.41	0.07	99.62	1.51	0.01
F_9	0.63	0.14	0.24	$\varphi(F_{1-9})$	8.55	0.41	0.06	99.64	1.52	0.01

beyond the seventh appears negligible since they do not have statistically significant risk premia, they have low Sharpe ratios and virtually no incremental contribution to the tangency portfolio and to any of the model's evaluation metrics. In essence, the remaining factors display low 'signal strenghts', and appear to be of second order importance.

Moreover, because we use RP-PCA to extract the factors, another important metric is the model's ability to span the cross-section of test assets. We find that, using a seven-factor model, none of the 60 portfolios have statistically significant average pricing errors at the 5% significance level. Also, given that factors F_2 to F_7 all have high signal

factor. Factors F_2 to F_7 seem to behave as cross-sectional factors, with strategy corner portfolios taking often exposures with opposite sign. For example, carry-P1 and carry-P5 have, respectively, negative and positive exposures to F_2.

strenghts and contribute to the tangency portfolio returns in a non-trivial magnitude, we do not consider more parsimonious models.

Taken together, these multiple pieces of evidence suggest that the currency SDF consists of seven factors. This is a larger model than the one uncovered by Nucera et al. (2024), which is not surprising given that the cross-section of test asset returns has expanded considerably with the addition of new option-based portfolio returns. Next, we turn to analyzing the risk exposures of the tradable HML factors to the latent factors, and in doing so we try to connect the latent factors to currency investment strategies, with a deeper focus on SRP_{HML}.

`Risk Exposures.` Table 4 reports the risk exposures, η, of the 12 HML factors to the first seven latent factors, together with the explained variations for models including an increasing number of factors. Aside from helping us interpret the sources of risks priced in the SDF, we note that the ηs are important objects in the three-pass procedure, as they map the latent factor risk premia onto the candidate factor risk premia. At the same time, the R^2s help quantify measurement errors in the candidate factors; for tradable factors measurement errors could reflect exposures to unpriced risk (e.g., non-diversifiable errors in the portfolio), or idiosyncratic risk that is not fully diversified (Giglio and Xiu, 2021; Giglio, Xiu, and Zhang, 2024).

The interpretation of the first four factors is fairly clearcut. While F_1 is close to a level "Dollar factor" (individual portfolios have similar positive risk exposures), it also helps explain a non-negligible share of time series variation of several investment strategies. The remaining factors are, however, of greater interest being slope, risk-premium factors. F_2 is a very important factor not only for Carry and RR, but also for currency strategies based on option information. The risks captured by F_2 are much less relevant for VAL and essentially negligible for momentum strategies. The lion's share of the explained variation of past-return strategies is captured by F_3 and F_4. Specifically, while F_3 is long on MOM strategies and short on the VAL strategy, F_4 behaves the opposite (except for MOMS).

Thus, F_1 is "Dollar factor", F_2 is a "Carry" factor, F_3 is a "Momentum" factor, and F_4 is "long Value short (medium/long-term) Momentum" factor. This evidence is largely in line with the one provided by Nucera et al. (2024), despite the two studies focus on substantially different samples. However, the inclusion of option strategies helps us refine the factors' interpretation, and requires interpretation of further factors F_5, F_6 and F_7.

Unlike the factors ordered before, F_5, F_6 and F_7 have a less clearcut interpretation. The risk exposures to these factors are generally negative for carry-related strategies (CAR, RR, NFA), but the contribution in terms of R^2 is relatively small for these tradable factors, as well as for other strategies capturing asymmetry or downside risks (SRP, VRPUD, VRPD). Instead, the contribution in terms of R^2 of F_5, F_6 and F_7 is most noticeable for MOMS and for some option-based risk-premium strategies, such as VRP

Table 4: Risk Exposures of Tradable Factors

The table presents the 12 tradable HML factors' exposures to the latent factors (A.I: Risk Exposures; η_{F_k}) and the explained variations (A.II: Explained Variations; $R^2_{F_{1-k}}$) obtained from the spanning regressions including an increasing number of factors, $k = 1, \ldots, 7$. Thus, we report the exposures to the first seven extracted, orthogonalized latent factors (i.e., $K = 7$). Latent factors are extracted by applying RP-PCA (with RP-weight $\omega = 20$) to the baseline sample of $N = 60$ portfolios obtained from the 11 currency investment strategies and the SRP strategy. Based on Newey-West standard errors, ***,**,* denote statistical significance at the 1-, 5- and 10-percent levels, respectively. The sample period is from February 1998 to December 2021, at monthly frequency.

	A.I: Risk Exposures						
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}
SRP	0.06***	0.40***	0.14***	0.16***	-0.12**	0.05	0.07
CAR	0.06***	0.51***	0.08***	0.13***	-0.15***	-0.08**	-0.05
RR	0.07***	0.49***	-0.18***	-0.02	-0.13***	-0.20***	-0.20***
NFA	0.10***	0.17***	0.04	0.32***	-0.18***	-0.26***	0.00
MOMS	-0.02	-0.10**	0.45***	0.34***	0.48***	0.17**	-0.57***
MOMM	-0.02	0.03	0.80***	-0.32***	-0.04	-0.20***	0.18***
MOML	-0.03*	0.04	0.81***	-0.44***	-0.10**	-0.03	0.04
VAL	0.03***	0.28***	-0.36***	0.38***	0.23**	0.41***	-0.10
VRP	0.05***	0.33***	-0.05	-0.28***	-0.39***	0.40***	-0.26***
VRPD	0.08***	0.44***	-0.02	-0.03	-0.30***	0.27***	-0.18***
VRPU	0.06***	0.39***	-0.04	0.17***	0.16***	-0.26***	0.28***
VRPUD	0.09***	0.52***	-0.03	0.10***	-0.20***	-0.13***	-0.15***
	A.II: Explained Variation						
	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$
SRP	19.70	72.94	75.57	77.60	78.65	78.72	78.92
CAR	14.31	83.28	84.02	85.09	86.30	86.58	86.65
RR	22.12	78.60	81.94	81.91	82.76	84.56	85.87
NFA	57.19	65.49	65.59	73.44	75.56	79.31	79.24
MOMS	1.77	4.46	31.48	40.23	55.71	57.27	72.18
MOMM	1.25	1.12	69.11	75.16	75.16	76.96	78.02
MOML	2.38	2.51	70.86	82.46	82.98	82.96	82.96
VAL	5.49	27.73	42.81	52.76	55.90	64.68	64.96
VRP	14.06	49.61	49.83	56.10	67.10	76.94	80.12
VRPD	30.07	82.31	82.29	82.27	87.78	91.43	92.74
VRPU	19.05	63.81	63.87	66.00	67.60	71.30	74.74
VRPUD	28.76	89.38	89.43	90.00	91.92	92.59	93.34

and VRPU. Hence, albeit being inherently weaker factors than the first factors, F_5, F_6 and F_7 are still useful to capture some of the residual sources of priced risks, mainly resulting from the addition of option strategies to the currency cross-section.

Of particular relevance for this study is the fact that SRP_{HML} displays positive and statistically significant exposures to all of the first four factors, thus being a procyclical factor with respect to these sources of risk. Only CAR shares the same feature. Indeed, notwithstanding the exact size of the currency SDF, these factors undoubtedly capture important sources of priced currency risk, capturing roughly three fourth of the tangency portfolio's Sharpe ratio. Next, we turn to analyze the risk-premium estimates which, among other things, allow us to shed further light on the connection between SRP_{HML} and the relevant, priced sources of currency risk.

`Risk Premia.` Table 5 presents the three-pass risk-premium estimates of the HML factors (λ_g). To assess the performance of the estimator, we can conveniently benchmark the estimates to the factor sample means (μ_g). Moreover, we can assess the behavior of de-noised factors, obtained by projecting the factor onto the space of the latent factors extracted via RP-PCA, using the η-exposure estimates. In essence, the de-noised candidate factor is a linear combination of the latent factors ($\hat{F}\hat{\eta}^{\top}$), whose sample average equals the three-pass risk-premium estimate ($\hat{\lambda}_g$). Figure A5 in the Internet Appendix presents cumulative returns of each of the 12 de-noised factors spanned by SDFs including at least 2 and up to 7 latent factors.

Using a seven-factor model, eight of the nine HML factors with significant average returns also have significant risk-premium estimates (the only exception being MOMM). The risk-premium estimates are close to sample means of the factors for many of the HML factors, but not for all of them. Specifically, the SRP_{HML} risk-premium estimate is close to the model-free estimate given by its mean (5.47% vs. 5.35%); however, the Sharpe ratio of the de-noised SRP_{HML} factor increases relative to the raw factor from 0.75 to 0.82. The risk premium estimate and Sharpe ratio for CAR are of particular interest in that they are lower (risk premium estimate of 4.9% vs. the mean of the CAR factor of 5.88%, and Sharpe ratio of 0.65 of the de-noised factor vs. 0.72 of the raw factor). In turn, this suggests that the true risk premium for CAR, i.e. the excess return that can be understood as compensation for systematic risk, is likely to be smaller than what is indicated by the average CAR excess return, and that the latter reflects idiosyncratic or unpriced risk. The opposite is true for SRP_{HML}, where the de-noised factor has a higher Sharpe ratio than the raw factor. This is because, even though the risk-premium estimate is very close to the factor mean, the de-noised factor displays a much lower standard deviation than the raw SRP_{HML} excess returns.

It is also useful to assess how the three-pass risk-premium estimates evolve as we add factors successively to the SDF. It is apparent that a two-factor model already delivers a satisfactory pricing performance for many strategies. For example, we can recover a large fraction of the CAR and, to a less extent, of the SRP_{HML} risk premia. However, this is clearly not the case for momentum strategies, whose estimated premia are far below their sample averages. At the same time, the two-factor model has a tendency to overestimate the premia of some of the other strategies (e.g., RR and VRP). When the third factor is added to the model, the premia of momentum strategies rise substantially (especially those of MOMM and MOML), consistent with F_3's interpretation as a momentum-like factor. Next, F_4 increases substantially the risk-premium estimate of VAL and MOMS (which doubles), while reducing those of MOMM and MOML. As we add F_5 to the model, the risk premia of most strategies drop, with the notable exception of the MOMS

Table 5: Risk Premia of Tradable Factors

The table presents the RP-PCA three-pass risk-premium estimates for the candidate HML tradable factors associated with the 12 currency investment strategies. Latent factors are extracted by applying RP-PCA (with RP-weight $\omega = 20$) to the baseline sample of $N = 60$ portfolios obtained from the 12 investment strategies. We implement RP-PCA using models of different dimension, denoted by SDFs with increasing number of factors, i.e., $\varphi(F_{1-k})$ with $k = 2, \ldots, 7$. For brevity, we omit to report the one-factor model results. For each model, we report the risk-premium estimates (λ_g); the asymptotic standard errors (se); and the Sharpe ratios (SR) associated with the projected factor, i.e., the return-based counterpart to the original candidate factor. For comparison, in the first panel (Model Free), we report the observed factor averages (μ_g), the associated standard errors (se), and the annualized Sharpe ratios (SR). ***,**,* denote significance, respectively, at the 1-, 5- and 10-percent levels. The sample period is from February 1998 to December 2021, at monthly frequency.

	Model Free			$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$		
	μ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR
SRP	5.47***	(1.63)	0.75	3.94***	(1.35)	0.63	4.72***	(1.39)	0.74	5.47***	(1.37)	0.85
CAR	5.88***	(1.79)	0.72	4.76***	(1.62)	0.64	5.23***	(1.64)	0.70	5.84***	(1.67)	0.78
RR	2.62	(1.89)	0.31	4.80***	(1.66)	0.63	3.77**	(1.71)	0.48	3.65**	(1.70)	0.47
NFA	2.80*	(1.61)	0.37	2.66**	(1.33)	0.43	2.90**	(1.35)	0.47	4.40***	(1.34)	0.68
MOMS	3.04*	(1.56)	0.40	-1.03**	(0.39)	-0.61	1.52	(1.04)	0.36	3.10***	(1.15)	0.64
MOMM	2.84*	(1.63)	0.34	-0.02	(0.61)	-0.02	4.51***	(1.54)	0.64	3.04*	(1.65)	0.41
MOML	1.73	(1.82)	0.20	0.02	(0.57)	0.01	4.61***	(1.56)	0.64	2.56	(1.69)	0.33
VAL	3.52**	(1.67)	0.44	2.70***	(1.01)	0.64	0.67	(1.16)	0.13	2.46*	(1.28)	0.42
VRP	1.32	(1.49)	0.18	3.24***	(1.07)	0.63	2.94***	(1.10)	0.57	1.64	(1.19)	0.30
VRPD	3.47**	(1.67)	0.43	4.50***	(1.55)	0.62	4.39***	(1.55)	0.60	4.27***	(1.58)	0.59
VRPU	3.98**	(1.62)	0.52	3.87***	(1.38)	0.63	3.66**	(1.37)	0.59	4.47***	(1.37)	0.71
VRPUD	4.10**	(2.00)	0.47	5.20***	(1.79)	0.62	5.03***	(1.80)	0.60	5.51***	(1.81)	0.66

	$\varphi(F_{1-5})$			$\varphi(F_{1-6})$			$\varphi(F_{1-7})$		
	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR
SRP	5.00***	(1.39)	0.77	5.15***	(1.42)	0.79	5.35***	(1.40)	0.82
CAR	5.29***	(1.69)	0.70	5.05***	(1.70)	0.67	4.90***	(1.71)	0.65
RR	3.16*	(1.72)	0.40	2.55	(1.78)	0.32	2.03	(1.78)	0.25
NFA	3.73***	(1.38)	0.56	2.95**	(1.46)	0.44	2.96*	(1.49)	0.44
MOMS	4.88***	(1.26)	0.87	5.39***	(1.30)	0.94	3.86**	(1.45)	0.60
MOMM	2.88*	(1.63)	0.39	2.28	(1.68)	0.31	2.75	(1.69)	0.37
MOML	2.17	(1.71)	0.28	2.07	(1.70)	0.27	2.18	(1.72)	0.28
VAL	3.33**	(1.36)	0.56	4.56***	(1.37)	0.71	4.29***	(1.45)	0.66
VRP	0.18	(1.30)	0.03	1.38	(1.34)	0.22	0.69	(1.35)	0.10
VRPD	3.14*	(1.65)	0.42	3.94**	(1.64)	0.51	3.45**	(1.64)	0.45
VRPU	5.08***	(1.39)	0.80	4.30***	(1.48)	0.66	5.06***	(1.47)	0.76
VRPUD	4.77**	(1.87)	0.56	4.39**	(1.91)	0.52	3.98**	(1.90)	0.47

and VRPU strategies. Thus, F_5 is a countercyclical source of risk for SRP_{HML}, unlike the first four factors. Finally, by including the additional factors F_6 and F_7, we notice variation in the risk-premium estimates for several strategies, consistent with the fact that these factors, while being ordered last because of their lower signal strengths, they are systematic sources of priced risk and many factors display significant exposures to them, as observed earlier.

5.2. Asset pricing tests

The three-pass analysis in the previous section delivers de-noised factors (see Figure A5). These de-noised factors can be interpreted as the excess returns of the candidate factors that can be expected in equilibrium on the basis of latent-factor SDF. Put simply, the sample mean of the de-noised factor is the factor's risk premium, while the sample mean of the raw factor is not necessarily equal to its risk premium.[30] Next, we use the de-noised HML factors in FMB and GMM asset pricing tests, in order to provide robust evidence about the strength and information content of the SRP factor.

Our earlier evidence from the RP-PCA three-pass procedure suggests an SDF with seven latent factors fully spans the information in the universe of 60 currency portfolio returns. The further analysis and interpretation of the latent factors points to a level factor and several slope factors. In this section, we attempt to price the full cross-section of 60 portfolio excess returns with low-dimensional SDFs that include de-noised HML factors. Among the slope factors, our prior evidence suggests that SRP_{HML} and a momentum-like factor should enter the currency SDF, given that the momentum HML factors appear to be largely uncorrelated with SRP_{HML}. We select MOMS as it singles out having more distinct properties from our SRP_{HML} factor, and hence is more likely to be required in the SDF. Recall that our preliminary analysis showed that MOMS is positively skewed, and is mildly negatively correlated with SRP_{HML}. Furthermore, the subsequent three-pass analysis showed that MOMS and SRP_{HML} risk exposures to the first-seven latent factors differ substantially.

Thus, to start with, we consider a parsimonious three-factor SDF including two slope factors, namely the de-noised SRP and MOMS HML factors, plus the DOL level factor (Table 6, Panel A). We find that the FMB regression delivers an estimate of the SRP_{HML} factor of about 4.49%, which is highly statistically significant and not different from the factor's sample average. The risk-premium estimate of the MOMS factor is 3.03%, which is also statistically significant and not different from the MOMS sample average. The cross-sectional adjusted R^2 is about 80%, which is lower than then 99% achieved by the optimal latent-factor SDF but nevertheless highly satisfactory, given the size and diversity of the cross-section of test asset returns. Furthermore, the GMM estimate of b_{SRP} is 0.011 with a t-statistic above 3, and the estimate of b_{MOMS} is about 0.008 with a t-statistic of 2.59. The χ^2 tests show that we cannot reject the null that all alphas are jointly statistically equal to zero (the FMB and GMM p-values are 0.52 and 0.38, respectively). In essence, this analysis suggests that the three-factor model featuring de-noised SRP_{HML} and MOMS as slope factors, performs well in pricing the full cross-section

[30]For example, Daniel et al. (2020) develop an alternative procedure to remove unpriced risk, i.e. risk that is not priced in equilibrium, from characteristic-sorted portfolios, using covariance information estimated from past returns. We rely on the three-pass procedure because it guarantees that the de-noised factors reflect all the relevant information that prices test asset returns.

Table 6: Pricing Currency Portfolios by SDFs

The table presents the results of the cross-sectional asset pricing tests using alternative SDFs with de-noised factors. In Panel A and B, we use three-factor SDFs: (A) Dollar factor (DOL), de-noised SRP and MOMS factors; (B) DOL, de-noised CAR, and MOMS factors. In Panel C and D, we use a four-factor SDF: (C) DOL, de-noised SRP and MOMS, plus de-noised CAR orthogonalized by SRP (CAR^o); (D) DOL, de-noised CAR and MOMS, plus de-noised SRP orthogonalized by CAR (SRP^o). Factors are de-noised using seven latent factors. The test assets consists of the 60 portfolios from the 12 investment strategies. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator, or the first-stage of the generalized method of moment (GMM) estimator. We also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). We also present the GMM estimates of the factor weights in the SDF, b. For FMB, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for GMM, we report the Newey-West t-statistics in brackets. We also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021 at a monthly frequency.

A. DOL, SRP, MOMS

A.I FMB

	DOL	SRP	MOMS	χ^2
λ	1.474	4.490	3.030	57.8
(NW)	(1.02)	(3.20)	(2.16)	[0.52]
(Sh)	(1.03)	(3.29)	(2.13)	

RMSE	*Adj* R^2
0.62	0.80

A.II GMM

	DOL	SRP	MOMS	χ^2
b	-0.001	0.011	0.008	61.7
	(-0.31)	(3.32)	(2.59)	[0.38]
λ	1.474	4.490	3.030	
	(1.04)	(3.28)	(2.18)	

B. DOL, CAR, MOMS

B.I FMB

	DOL	CAR	MOMS	χ^2
λ	1.476	4.852	3.030	62.8
(NW)	(1.03)	(3.09)	(2.16)	[0.34]
(Sh)	(1.03)	(3.09)	(2.14)	

RMSE	*Adj* R^2
0.67	0.77

B.II GMM

	DOL	CAR	MOMS	χ^2
b	0.000	0.008	0.008	64.5
	(0.14)	(3.22)	(2.72)	[0.29]
λ	1.476	4.852	3.030	
	(1.04)	(3.04)	(2.18)	

C. DOL, SRP, MOMS, CAR^o

A.I FMB

	DOL	SRP	MOMS	CAR^o	χ^2
λ	1.472	4.896	2.793	-0.573	47.6
(NW)	(1.02)	(3.52)	(2.03)	(-1.56)	[0.83]
(Sh)	(1.03)	(3.63)	(1.99)	(-1.58)	

RMSE	*Adj* R^2
0.56	0.84

A.II GMM

	DOL	SRP	MOMS	CAR^o	χ^2
b	-0.004	0.013	0.006	-0.024	54.6
	(-1.20)	(3.89)	(1.74)	(-1.56)	[0.60]
λ	1.472	4.896	2.793	-0.573	
	(1.04)	(3.62)	(2.01)	(-1.48)	

D. DOL, CAR, MOMS, SRP^o

B.I FMB

	DOL	CAR	MOMS	SRP^o	χ^2
λ	1.471	5.054	2.805	0.679	48.8
(NW)	(1.02)	(3.23)	(2.03)	(2.15)	[0.80]
(Sh)	(1.02)	(3.23)	(2.00)	(2.18)	

RMSE	*Adj* R^2
0.56	0.84

B.II GMM

	DOL	CAR	MOMS	SRP^o	χ^2
b	-0.004	0.010	0.006	0.039	54.5
	(-1.18)	(3.82)	(1.77)	(2.04)	[0.61]
λ	1.471	5.054	2.805	0.678	
	(1.04)	(3.15)	(2.01)	(1.99)	

of 60 test assets.

To visually inspect the model's pricing accuracy, Figure 4 shows the portfolio model-implied excess returns (x-axis) vs. the observed mean excess returns (y-axis). In addition to the 60 portfolios (Panel D), we also consider several smaller cross-sections, including

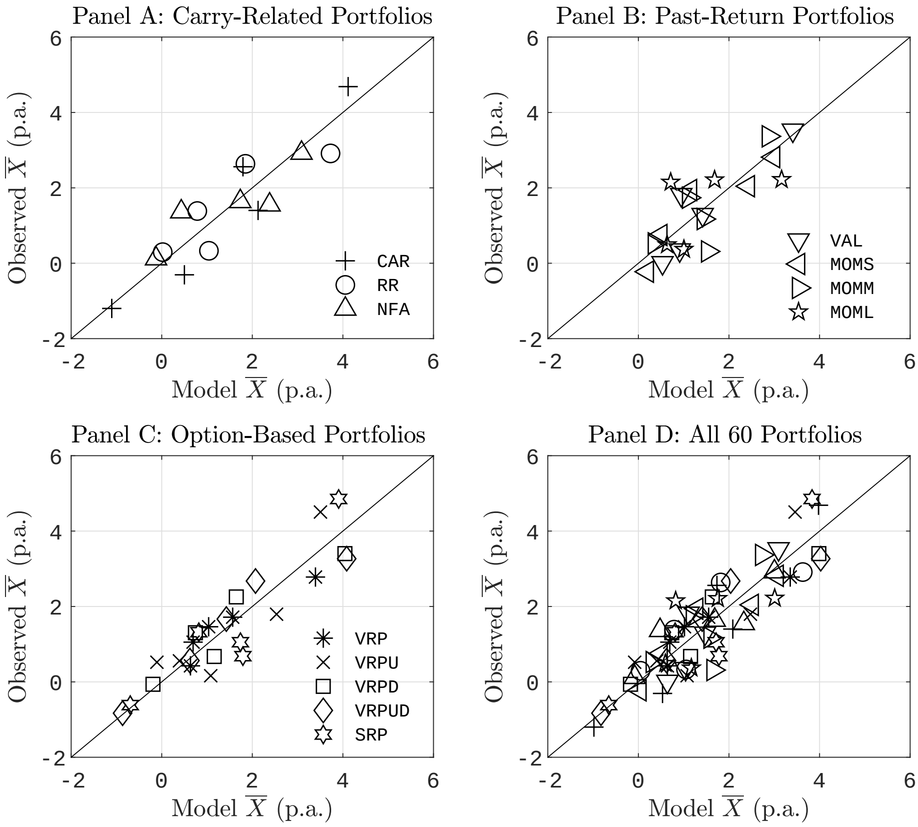

Figure 4: Observed vs. Model-Implied Expected Returns

The figure shows the observed, realized mean excess returns versus the two-pass model-implied mean excess returns obtained from the three-factor SDF, including the Dollar factor (DOL) and de-noised SRP and MOMS HML factors (i.e., estimates from Table A8). Factors are de-noised using seven latent factors. Each panel refers to a different cross-section, including the portfolios from the indicated strategies. Specifically, we use the following cross-sections of test assets: (A) the 15 portfolios from the CAR, NFA, and RR strategies; (B) the 20 portfolios from the MOMS, MOMM, MOML, and VAL strategies; (C) the 25 portfolios from the VRP, VRPU, VRPD, VRPUD, and SRP strategies; (D) the 60 portfolios from pooling together the portfolios in A, B, and C. In each cross-section, we also include the de-noised SRP and MOMS factors as additional test assets. Excess returns are in percent, annualized (p.a.). The sample period is from February 1998 to December 2021 at monthly frequency.

15 CAR-related portfolios (Panel A), 20 past return-related portfolios (Panel B), and 25 option-based risk-premium portfolios (Panel C).[31] The main takeaway is that, the average test asset returns lie around the 45-degree line, suggesting a very accurate pricing performance.

`SRP`$_{HML}$ `vs CAR comparison.` We then ask whether replacing the SRP$_{HML}$ factor with the CAR factor achieves the same satisfactory performance. Hence, Table 6, Panel B

[31] The FMB and GMM estimates resulted from those cross-sections of portfolios are provided in Table A8, in the Internet Appendix. Results are rather stable across cross-sections, with SRP displaying t-statistics of both λs and bs above 3. R^2s are around 85% for carry-related and option-related cross-sections (A and B), and somewhat lower for the past return-related cross-section (C).

presents the results from using a three-factor model comprising the de-noised CAR and MOMS factors, in addition to the DOL level factor. The results are qualitatively identical to the ones reported in Panel A, displaying minor quantitative differences as the adjusted R^2 and the p-values of the χ^2 tests are lower when using CAR rather than SRP_{HML}. This is not entirely surprising given that SRP_{HML} and CAR are highly correlated factors. Therefore, to avoid multicollinearity problems that prevent us from having both SRP_{HML} and CAR in the SDF, we address the question of whether CAR or SRP_{HML} performs better in pricing by isolating the orthogonal information in these two factors. Specifically, we consider two four-factor SDFs: one that includes DOL, SRP_{HML}, MOMS and the orthogonal component of CAR with respect to SRP_{HML}, i.e. CAR^o (results in Panel C); and another that includes DOL, CAR, MOMS and the orthogonal component of SRP_{HML} with respect to CAR, i.e. SRP^o (results in Panel D).

The results are very clear. Panel C of Table 6 shows that CAR^o does not contain extra pricing information beyond SRP_{HML} and MOMS (Panel C), since it has a negative and statistically insignificant risk premium (both using FMB and GMM) and a statistically insignificant factor loading in the SDF. In stark contrast, Panel D shows that SRP^o displays a positive and statistically significant risk premium, and enters the SDF with a sizable and statistically significant loading. In essence, this evidence makes clear that, while SRP_{HML} and CAR are highly correlated, SRP_{HML} displays stronger pricing power than CAR and fully subsumes the information in CAR, whereas the orthogonal information in SRP_{HML} beyond CAR contains price-relevant information.[32] The logical conclusion implied by these results is that SRP_{HML} enters the currency SDF, alongside a momentum factor like MOMS and a level factor like DOL.

6. Additional Analysis and Robustness

To complete the analysis, we perform a number of additional exercises, some of which are presented in detail in the Internet Appendix. The main results can be summarized as follows. First, we find that the inclusion of SRP portfolios in the cross-section of test assets from which we extract the latent factors is not central to the recovery of the SRP_{HML} risk premium, which is symptomatic of a rather strong factor (see, Giglio, Xiu, and Zhang, 2024).[33] By contrast, other factors, e.g., currency value, also have relatively high risk premia (and Sharpe ratios), but they appear to be much weaker factors, being relevant only for a small set of test assets. Indeed, an accurate recovery of their risk

[32] To lend further support to this finding, we also estimate spanning regressions, in the sense of Barillas and Shanken (2017), for SRP_{HML} and CAR using de-noised factors. We find that SRP_{HML} fully explains CAR, while the opposite is not the case. In fact, CAR is unable to explain roughly one fourth of the SRP_{HML} Sharpe ratio (i.e., the unexplained Sharpe ratio is around 0.2). Thus, it is clear that the information in CAR does not subsume the information in SRP_{HML}, either statistically or economically.

[33] For brevity, we do not report these findings, but they are available upon request.

premia can only be achieved by including the strategy portfolios in the set of test assets. It is also important to note that we find that by excluding the SRP portfolios from the cross-section, the maximal Sharpe ratio of the tangency portfolio spanned by the latent factors decreases slightly. Thus, by investing also in the SRP portfolios, one moves closer to the currency mean-variance efficient frontier, consistent with the asset pricing tests showing that the information in SRP_{HML} is not entirely spanned by the competing factors.

Second, we assess how the SRP nontradable factor behaves in the three-pass estimation (Section V in the Internet Appendix). Despite the evident appeal of working with nontradable factors, the estimation of their risk premia is notoriously cumbersome. A model-free estimate of their risk premium is not readily available, and they are often measured with large errors, resulting in a low signal-to-noise ratio (e.g., Adrian, Etula, and Muir, 2014). This can in turn distort the two-pass inference, making the use of the three-pass procedure highly desirable (Giglio and Xiu, 2021). We find that the three-pass estimate of the SRP_{NT} risk premium is economically large and statistically significant (at the 5% level), and the Sharpe ratio of the de-noised return-based SRP_{NT} is also high. Moreover, we show that also using a parsimonious three-factor SDF, including de-noised SRP_{NT} (instead of SRP_{HML}) and MOMS, plus DOL, the pricing perfomance using standard asset pricing tests remains very accurate. Overall, SRP_{NT} qualitatively behaves like its tradable counterpart, SRP_{HML}.[34]

Finally, we perform the two-pass asset pricing tests using the raw, noisy factors (Section VI in the Internet Appendix). The resulting evidence is largely robust to the evidence documented earlier using de-noised factors. A three factor SDF, including DOL, SRP_{HML} and MOMS, prices the 60 test assets. The pricing performance remains accurate also when replacing SRP_{HML} with SRP_{NT}. Moreover, the results are virtually unchanged regardless of whether we include the five SRP portfolios in the cross-section of test assets.

7. Conclusion

We propose a novel, model-free measure of currency skewness risk premium (SRP), and show that buying currencies with a high SRP and selling currencies with a low SRP generates high returns and Sharpe ratio. The resulting long-short factor, SRP_{HML}, enters the currency pricing kernel and is central to the pricing of risks inherent in many currency strategies. This evidence emerges using the broadest cross-section of portfolio currency

[34]By contrast, we find that some other option-based nontradable factors commonly used to capture volatility, tail, and uncertainty risks in foreign exchange and other markets (including the equity tail-risk factor of Fan, Londono, and Xiao, 2022) are not priced in our cross-section, as their risk premia, albeit correctly signed (i.e., are countercyclical sources of risk), are not statistically significant once one accounts for omitted-variable and measurement-error biases.

excess returns studied in this literature, and employing robust asset pricing methods which control for omitted variables and measurement errors. The results, taken together, show that skewness risk is a strong and priced source of currency risk, consistent with the notion that investors in currency markets dislike skewness risk and hence are willing to pay a premium to ensure against skewness fluctuations. Therefore, these findings lend novel empirical support to the theoretical asset pricing models assigning a specific role to rare disasters and skewness risk in driving asset returns.

This analysis contributes to the understanding of the macro-financial sources of risk driving the currency pricing kernel, highlighting the prominent role played by investors' aversion to skewness risk. This is a valuable contribution to the currency literature as most of the studies have mainly focused on carry (e.g., Burnside et al., 2011; Jurek, 2014) and/or have used measures of crash risk derived from other markets (e.g., Lettau et al., 2014; Fan et al., 2022). At the same time, our skewness risk premium factor features substantially different properties from the volatility risk premium factor of Della Corte et al. (2016), suggesting that what ultimately matters for pricing currency risk is investors' aversion to the asymmetry in the return distributions.

Future research could study the deeper underlying drivers of aversion to skewness, and in this respect it would seem fruitful to investigate the potential relationship between currency skewness risk and macro risk, for example, related to sharp movements in inflation and economic activity. Furthermore, while separate strands of the literature study the pricing role of skewness risk factors in specific asset classes, it seems important to unify these strands by analyzing the pricing ability of aggregate skewness risk across asset classes. Finally, further research could deploy our measure on high-frequency spot and shorter-term option FX data in order to disentangle accurately the impact of leverage and of asymmetric jumps both in terms of predicting the cross-section of currency returns and in terms of pricing power, as well as exploit the information content of the full term structure of option prices.

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Internet Appendix
(not for publication)

Skewness Risk Premia and the Cross-Section of Currency Returns

Table of Contents:

I. Risk-Neutral Variance and Semivariances

To construct the option implied variances and semivariances, we need to evaluate these two integrations numerically,

$$IV^+_{i,t} \;=\; \int_{S_{i,t}}^{\infty} \frac{2\Big(1-\log(\frac{K_i}{S_{i,t}})\Big)}{K_i^2} C(t,\tau;K_i)dK_i, \tag{I.1}$$

$$IV^-_{i,t} \;=\; \int_{0}^{S_{i,t}} \frac{2\Big(1+\log(\frac{S_{i,t}}{K_i})\Big)}{K_i^2} P(t,\tau;K_i)dK_i. \tag{I.2}$$

For this purpose, we discretize the respective integrals and approximate them from available options, similar to Jiang and Tian (2005) at each time t. In what follows we detail the main steps.

`Step 1: Constructing Data.` At each time t, our data include Garman and Kohlhagen (1983) implied volatility quotes for five different combinations of plain-vanilla options: at-the-money (ATM) delta-neutral straddles, 10 delta and 25 delta risk-reversals, and 10 delta and 25 delta butterfly spreads. From these data, we can recover implied volatilities (iv_t) and strikes (K_t) for call and put options with deltas of 10, 25, and 50. Define the moneyness as $M_t = K_t/S_t$ and denote the options data at time t as $O_t = [iv_t, M_t]$, which are then sorted along moneyness from low to high.

`Step 2: Constructing Grids.` We consider a total of 1,001 grid points in the moneyness ranging from 1/3 to 3. For those moneyness grids inside the available moneyness range, $[M_{t,min}, M_{t,max}]$, we use the cubic splines based on option data O_t to interpolate the corresponding implied volatilities. For those moneyness grids beyond the available range, we use endpoint implied volatility to extrapolate their implied volatilities: the implied volatilities for all moneyness grids larger than $M_{t,max}$ are set to $iv_t(M_{t,max})$ and the implied volatilities for all moneyness grids smaller than $M_{t,min}$ are set to $iv_t(M_{t,min})$. Denote the moneyness grids and the resulted interpolated/extrapolated implied volatilities as M_o and iv_o, respectively.

`Step 3: Recovering Option Prices.` From the above interpolated/extrapolated implied volatilities, denote the out-of-the-money call options as $C_{t,otm} = [iv_o(M_o > 1), M_o(M_o > 1)]$ and the out-of-the-money put options as $P_{t,otm} = [iv_o(M_o < 1), M_o(M_o < 1)]$. We then calculate the corresponding out-of-the-money call and put prices using the Garman and Kohlhagen (1983).

`Step 4: Discretizing Integrals.` Based on the above out-of-the-money call and put option prices, we approximate the integrals in Eqs. (I.1) and (I.2), respectively, relying on the trapezoidal rule. As a result, we obtain approximated upside and downside risk-neutral semivariances, $IV^+_{i,t}$ and $IV^-_{i,t}$, and the risk-neutral variance is simply given by $IV_{i,t} = IV^+_{i,t} + IV^-_{i,t}$.

II. Data and Summary Statistics

Table A1: List of Currencies

This table lists the 28 currencies used in the empirical analysis, indicating the currency identifier/code, name, as well as the start and end dates for each currency. We follow Kroencke et al. (2014), Della Corte et al. (2016) and Nucera et al. (2024), among others, and leave out the indicated countries for the following periods: Indonesia (01/01/1998 – 31/07/1998; 01/02/2001 – 31/05/2005); Malaysia (01/05/1998 – 30/06/2005); Russia (01/12/2008 – 30/01/2009; 03/11/2014 – 27/02/2015); South Africa (01/08/1985 – 30/08/1985; 01/01/2002 – 31/05/2005); Turkey (01/11/2000 – 30/11/2001).

Code	Names	Start	End
AUD	Australian Dollar	1998-01	2021-12
BRL	Brazilian Real	2007-10	2021-12
CAD	Canadian Dollar	1998-01	2021-12
CHF	Swiss Franc	1998-01	2021-12
CZK	Czech Koruna	1998-01	2021-12
DKK	Danish Kroner	1998-01	2021-12
EUR	European Euro	1999-01	2021-12
GBP	British Pound	1998-01	2021-12
HKD	Hong Kong Dollar	1998-01	2021-12
HUF	Hungarian Forint	2001-08	2021-12
IDR	Indonesian Rupiah	2005-06	2021-12
ILS	Israeli Sheqel	2004-03	2021-12
INR	Indian Rupee	2004-03	2021-12
JPY	Japanese Yen	1998-01	2021-12
KRW	Korean Won	2004-07	2021-12
MXN	Mexican Peso	1998-01	2021-12
MYR	Malaysian Ringgit	2005-07	2021-12
NOK	Norwegian Krone	1998-01	2021-12
NZD	New Zealand Dollar	1998-01	2021-12
PHP	Philippine Peso	2003-09	2021-12
PLN	Polish Zloty	2002-02	2021-12
RUB	Russian Ruble	2006-01	2021-12
SEK	Swedish Krona	1998-01	2021-12
SGD	Singapore Dollar	2000-07	2021-12
THB	Thai Baht	2005-01	2021-12
TRY	Turkish Lira	2006-07	2021-12
TWD	Taiwan Dollar	1998-06	2021-12
ZAR	South African Rand	1998-01	2021-12

Table A2: Summary Statistics

The table presents the summary statistics of average currency returns, skewness risk premia, realized variance/semivariances, and implied variance/semivariances. Our sample contains spot and one-month forward exchange rates and currency options with respect to the U.S. dollar for 28 currencies. Realized measures are constructed using the previous 3-month daily spot rates and implied measures are constructed using 3-month at-the-money delta-neutral straddles, 10 delta and 25 delta risk-reversals, and 10 delta and 25 delta butterfly spreads. In Panel A, CRet and SRP denote monthly currency returns and skewness risk premia, respectively. In Panels B and C, we present realized and implied variances/semivariances and express their statistics in percentage (except skewness and kurtosis). The sample period is from January 1998 to December 2021.

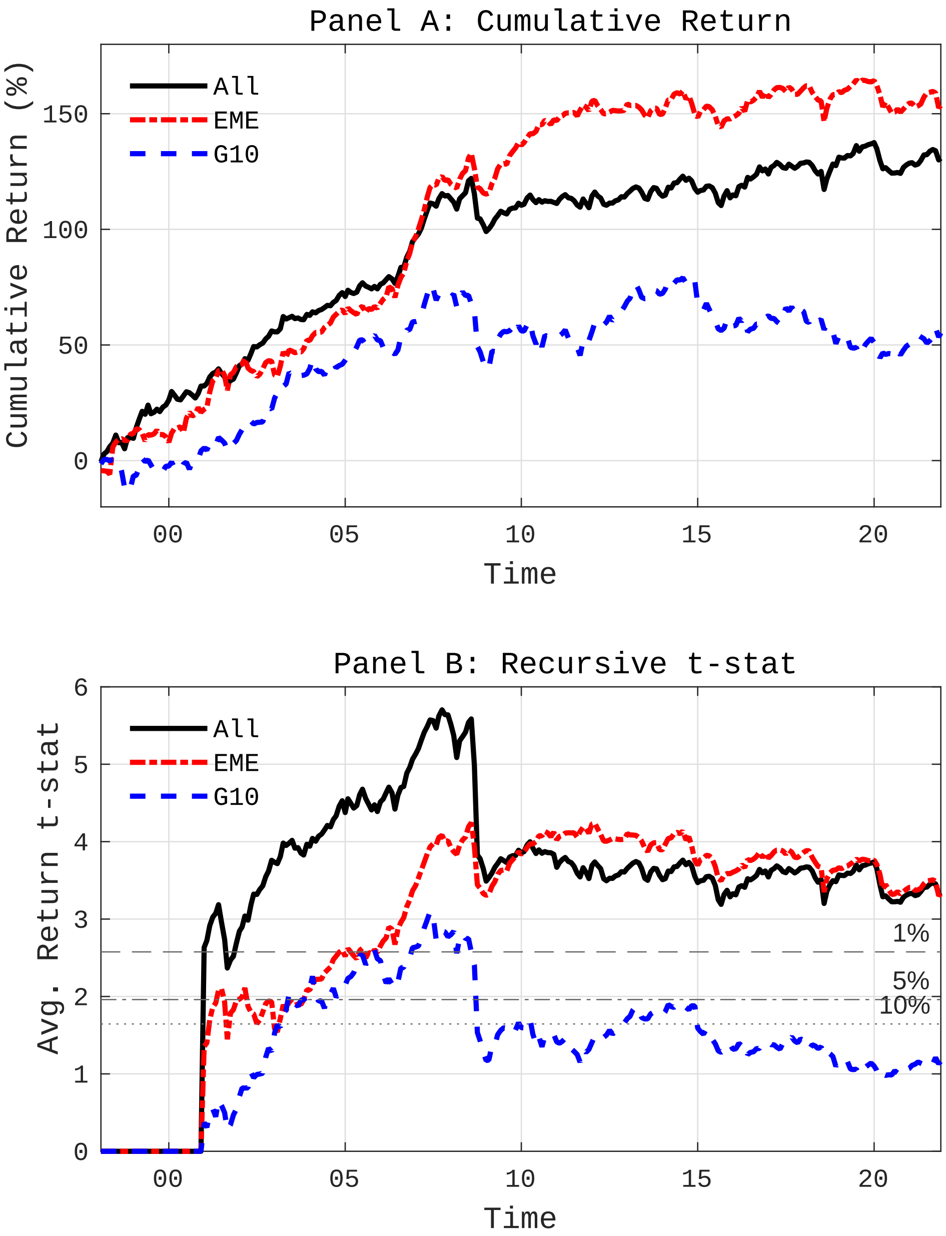
	A. Returns&SRP		B. Realized Measures			C. Implied Measures		
	CRet	SRP	RV	RVU	RVD	IV	IVU	IVD
Mean	0.013	0.165	1.067	0.524	0.543	1.501	0.490	1.011
STD	0.105	0.333	1.699	0.853	0.878	2.105	0.474	1.720
Skew	-0.374	-0.327	8.043	8.192	8.165	8.763	4.518	9.711
Kurt	7.222	3.591	109.1	113.3	110.7	141.8	42.38	168.6
Q05	-0.549	-0.392	0.041	0.020	0.019	0.149	0.061	0.051
Q50	0.008	0.165	0.678	0.329	0.337	1.029	0.390	0.572
Q95	0.594	0.704	3.229	1.567	1.649	4.212	1.210	3.125

Table A3: SRP Portfolios: G10 and Emerging Market Currency Samples

The table presents the performance of the portfolios constructed by sorting currencies on their currency skewness risk premia (SRP). At the end of each month, we allocate currencies to five portfolios using as signals (or sorting variable) their individual SRPs. Specifically, we allocate 20% of currencies with the lowest SRPs to Portfolio 1 (P1) and 20% of currencies with the highest SRPs to Portfolio 5 (P5). We then form a spread portfolio (HML) that longs P5 and shorts P1. We hold these portfolios to the next month and compute their realized mean excess returns. Panel A uses a small cross-section of G10 currencies, i.e., AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD, SEK; and Panel B uses the cross-section of the 18 emerging currencies. The Newey-West t-statistics are presented in brackets. The sample period is from January 1998 to December 2021 at a monthly frequency.

	Panel A: G10 Currencies					
	P1	P2	P3	P4	P5	HML
Mean	-0.25	1.11	-0.20	1.25	2.06	2.31
	(-0.14)	(0.58)	(-0.10)	(0.62)	(0.93)	(1.14)
STD	8.09	8.69	9.23	9.70	10.3	9.07
SR	0.03	0.13	0.02	0.13	0.20	0.25
Skew	0.53	0.15	0.14	-0.37	-0.31	-0.96
Kurt	4.15	3.74	4.43	3.89	4.62	7.37
	Panel B: 18 Emerging Currencies					
	P1	P2	P3	P4	P5	HML
Mean	-0.66	2.02	0.37	2.16	5.76	6.42
	(-0.58)	(1.18)	(0.20)	(1.08)	(2.62)	(3.26)
STD	5.44	8.03	8.98	10.0	9.29	8.55
SR	0.12	0.25	0.04	0.21	0.62	0.75
Skew	-1.34	-0.17	-0.90	-0.25	-0.63	-0.10
Kurt	14.9	5.32	6.66	5.80	4.60	5.45

Figure A1: SRP HML Factors by Currency Samples



The figure shows the SRP_{HML} factors for the three groups of currencies: All, G10, and EME (see Tables 1 and A3). Panel A presents the SRP factors cumulative excess returns, while Panel B shows the recursive t-statistics (based on the Newey-West standard errors) of the average excess returns over expanding windows.

III. Currency Investment Strategies

`FX Investment Strategies`. Next, we describe the currency investment strategies that deliver the portfolios (i.e., test assets) and HML factors (i.e., candidate tradable risk factors) under investigation in our empirical analysis. Importantly, for a given strategy or signal, we allocate currencies to the five portfolios such that, as we move from P1 to P5, the portfolios include countries of increased risk in the sense that the HML portfolio has a positive average return (see Table 1 and Table A4).

`Skewness Risk-Premium Strategy (SRP)`. We allocate currencies to portfolios as detailed in Section 3. Thus, at the end of each month t, we allocate currencies with low SRPs to portfolio 1 (P1) and currencies with high SRPs to portfolio 5 (P5). Portfolios are rebalanced monthly. FX and interest rate data are from from Barclays Bank International (BBI), Reuters and WM/Reuters accessed via Datastream, while the option data are from a large investment bank.

`Carry (CAR)`. At the end of each month t, currencies are allocated to five portfolios according to their forward discounts $fd_{it} = (S_{it} - F_{it})/S_{it}$, where S_{it} and F_{it} are the spot and forward exchange rate mid-quotes for foreign currency i, respectively (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). While P1 collects the currencies with the lowest forward discounts, P5 collects currencies with the highest forward discounts. Therefore, P1 (P5) contains the currencies with the lowest (highest) interest rate differential relative to the United States, assuming that CIP holds. Portfolios are rebalanced monthly. Data are from from Barclays Bank International (BBI), Reuters and WM/Reuters accessed via Datastream.

`Net Foreign Assets (NFA)`. Following Della Corte et al. (2016), at the end of each month t, currencies are allocated into portfolios according to the ratio between the foreign country's net foreign assets (NFA) and the country's gross domestic product (GDP), both denominated in U.S. dollar. Specifically, P1 includes creditor currencies, i.e., those with the highest NFA to GDP ratios, whereas P5 includes debtor currencies, i.e., those with the lowest NFA to GDP ratios. Portfolios are rebalanced monthly and NFA are lagged to account for the delay in the data releases. We therefore use the latest available data so that the strategy is tradable in real time. We thank Gian Maria Milesi-Ferretti to kindly share with us the updated version of the data on foreign assets and liabilities previously used in Lane and Milesi-Ferretti (2004) and Lane and Milesi-Ferretti (2007); we refer to these studies for a detailed description of the data.

`Risk Reversal (RR)`. Following Della Corte et al. (2016) and Della Corte et al. (2022), at the end of each month t, currencies are allocated into portfolios according to the risk reversals. We define the risk reversal as the three-month currency option implied volatility difference between the out-of-the-money (10 delta) call options and the out-of-the-money (10 delta) put options. Specifically, currencies with the highest risk reversals (i.e., low risk currencies in the sense that are more likely to experience strong appreciations) are allocated to P1, while currencies with the lowest risk reversals (i.e., high risk currencies in the sense that are more likely to experience strong depreciations) are allocated to P5. While this strategy also uses signals inferred from option data, it rests on risk-neutral signals, unlike the other option-based strategies considered in this study that use risk premia as signals (e.g., VRP).

`Momentum (MOMS, MOMM and MOML)`. At the end of each month t, we form portfolios based on excess returns realized over the previous m months (e.g., Asness et al., 2013;

Menkhoff et al., 2012b). Thus, the strategies differ in the formation period used to construct the past excess-return signal. Specifically, to construct short-, medium- and long-term momentum portfolios, we use the previous month ($m = 1$), six-month ($m = 6$), and 12-month ($m = 12$) past excess returns. Thus, P1 contains the currencies with the lowest short-term excess returns – the loser currencies – and P5 contains the currencies with the highest short-term excess returns – the winner currencies. Unlike previous currency studies (e.g., Nucera et al., 2024), we consider also medium-term momentum, largely in line with the equity literature. Portfolios are rebalanced monthly. Data are from from Barclays Bank International (BBI), Reuters and WM/Reuters accessed via Datastream.

`Currency Value (VAL)`. At the end of each month t, currencies are allocated to portfolios based on the lagged five-year nominal exchange rate return. Thus, we consider a simpler measure of currency value as we use nominal instead of real returns, whereby the latter exploits deviations from the relative purchasing power parity (e.g., Asness et al., 2013; Kroencke et al., 2014; Menkhoff et al., 2017). This is because for many of the currencies considered consumer price index data are very poorly measured or are not, or seldomly, available. Moreover, these earlier studies document that the variability in the value signals are mostly determined by the nominal exchange rate component. Specifically, P1 contains over-valued currencies, i.e., those with the highest lagged nominal exchange rate return, and P5 contains under-valued currencies, i.e., those with the lowest lagged nominal exchange rate return. Portfolios are rebalanced every month. Portfolios are rebalanced monthly. Data are from from Barclays Bank International (BBI), Reuters and WM/Reuters accessed via Datastream.

`Option-Based Risk-Premium Strategies (VRP, VRPU, VRPD, and VRPUD)`. At the end of each month t, currencies are allocated to portfolios based on the selected lagged risk premium measure employed, which are defined as in Section 3. Specifically, for the variance risk premium (VRP) strategy we allocate to P1 currencies with high VRPs and to P5 currencies with low VRPs (thus we employ an opposite sorting scheme from Della Corte et al., 2016 to allocate currencies to portfolios, so that the HML portfolio has positive average returns); for the upside VRP (VRPU) strategy we allocate to P1 currencies with low VRPUs, while to P5 currencies with high VRPUs; for the downside VRP (VRPD) strategy we allocate to P1 currencies with high VRPDs and to P5 currencies with low VRPDs; for the asymmetry (VRPUD) – upside minus downside VRP – strategy we allocate to P1 currencies with low VRPUDs and to P5 currencies with high VRPUDs. Portfolios are rebalanced monthly. FX and interest rate data are from from Barclays Bank International (BBI), Reuters and WM/Reuters accessed via Datastream, while the option data are from a large investment bank.

Table A4: Performance of Currency Investment Strategies

The table presents the performance and risk of the portfolios constructed based on 11 signals other than SRP (which are instead reported in Table 1). We refer to the text in Section III for a detailed description of the sorting scheme and signal employed to construct each of the investment strategies considered. For a given strategy, we form a long-short portfolio, or simply HML factor, that longs Portfolio 5 and shorts Portfolio 1. The Newey-West t-statistics are presented in brackets, and the skewness of portfolios are presented in square brackets. The sample period is from February 1998 to December 2021.

	P1	P2	P3	P4	P5	HML	SR
CAR	-1.20	-0.31	2.56	1.40	4.69	5.88	0.72
	(-0.86)	(-0.21)	(1.51)	(0.73)	(2.23)	(3.27)	
	[0.19]	[-0.10]	[-0.14]	[-0.44]	[-0.69]	[-0.47]	
NFA	0.12	1.37	1.64	1.55	2.92	2.80	0.37
	(0.11)	(0.81)	(1.01)	(0.89)	(1.27)	(1.68)	
	[0.16]	[-0.14]	[0.22]	[-0.66]	[-0.66]	[-0.93]	
RR	0.29	1.39	0.33	2.64	2.91	2.62	0.31
	(0.22)	(0.81)	(0.20)	(1.58)	(1.32)	(1.36)	
	[0.62]	[0.08]	[-0.20]	[-0.39]	[-0.61]	[-0.51]	
VRP	1.46	1.05	0.43	1.72	2.78	1.32	0.18
	(0.95)	(0.76)	(0.24)	(1.00)	(1.34)	(0.89)	
	[-0.12]	[-0.12]	[-0.18]	[-0.04]	[-0.85]	[-0.65]	
VRPU	0.52	0.56	0.16	1.80	4.51	3.98	0.52
	(0.34)	(0.37)	(0.11)	(0.98)	(2.03)	(2.41)	
	[-0.04]	[-0.04]	[-0.10]	[-0.52]	[-0.50]	[-0.47]	
VRPD	-0.06	1.30	0.67	2.25	3.40	3.47	0.43
	(-0.05)	(1.00)	(0.36)	(1.24)	(1.55)	(2.10)	
	[0.26]	[0.18]	[-0.22]	[-0.35]	[-0.77]	[-0.81]	
VPUD	-0.83	0.56	1.67	2.68	3.27	4.10	0.47
	(-0.61)	(0.42)	(0.99)	(1.42)	(1.42)	(2.01)	
	[0.20]	[-0.17]	[-0.08]	[-0.49]	[-0.72]	[-0.68]	
MOMS	-0.22	0.75	1.94	2.04	2.81	3.04	0.40
	(-0.12)	(0.43)	(1.11)	(1.28)	(1.70)	(1.99)	
	[-0.63]	[-0.56]	[-0.13]	[0.15]	[-0.02]	[0.52]	
MOMM	0.53	1.74	1.17	0.31	3.37	2.84	0.34
	(0.27)	(1.02)	(0.82)	(0.19)	(1.81)	(1.75)	
	[0.00]	[-0.36]	[0.14]	[-0.34]	[-0.63]	[0.01]	
MOML	0.49	2.15	0.37	2.21	2.22	1.73	0.20
	(0.24)	(1.38)	(0.22)	(1.35)	(1.24)	(0.94)	
	[0.08]	[0.00]	[-0.05]	[-0.45]	[-0.67]	[-0.10]	
VAL	0.01	1.82	0.35	1.29	3.53	3.52	0.44
	(0.01)	(1.21)	(0.22)	(0.74)	(1.75)	(2.11)	
	[-0.48]	[-0.09]	[-0.20]	[-0.34]	[-0.03]	[-0.07]	

Table A5: Portfolio Constituents

The table presents the top five constituents of the corner portfolios – the low-risk P1 and the high-risk P5, for each of the currency investment strategies considered. Specifically, the top constituents are those that display the highest time series frequency (Freq) of appearance in the selected portfolio.

A. SRP				B. CAR			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
SGD	0.43	ZAR	0.50	DKK	0.35	INR	0.52
TWD	0.47	INR	0.55	CZK	0.37	IDR	0.53
CHF	0.69	MXN	0.60	TWD	0.59	MXN	0.61
HKD	0.73	IDR	0.61	JPY	0.85	TRY	0.64
JPY	0.89	TRY	0.61	CHF	0.86	ZAR	0.77
C. RR				**D. VRP**			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
EUR	0.34	IDR	0.48	NZD	0.28	BRL	0.41
TWD	0.47	BRL	0.52	CHF	0.31	TRY	0.48
CHF	0.72	TRY	0.53	CAD	0.34	IDR	0.53
HKD	0.73	MXN	0.74	SGD	0.37	MXN	0.61
JPY	0.86	ZAR	0.82	HKD	0.69	ZAR	0.62
E. VRPU				**F. VRPD**			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
DKK	0.32	BRL	0.40	TWD	0.31	BRL	0.51
CZK	0.32	HUF	0.42	SGD	0.41	IDR	0.52
SEK	0.37	MXN	0.42	CHF	0.62	TRY	0.52
CHF	0.50	TRY	0.45	JPY	0.62	MXN	0.68
JPY	0.71	ZAR	0.53	HKD	0.66	ZAR	0.82
G. VPUD				**H. NFA**			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
SGD	0.36	IDR	0.52	NOK	0.69	TRY	0.55
HKD	0.40	BRL	0.55	TWD	0.85	PLN	0.69
TWD	0.43	TRY	0.55	SGD	0.90	HUF	0.85
CHF	0.83	MXN	0.68	CHF	1	AUD	1
JPY	0.92	ZAR	0.85	HKD	1	NZD	1
I. VAL				**J. MOMS**			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
NZD	0.33	BRL	0.33	CHF	0.23	JPY	0.23
HKD	0.36	RUB	0.47	AUD	0.23	CZK	0.24
JPY	0.37	TRY	0.54	ZAR	0.24	AUD	0.25
CZK	0.44	ZAR	0.56	HKD	0.25	MXN	0.28
CHF	0.49	MXN	0.67	JPY	0.37	NZD	0.29
K. MOMM				**L. MOML**			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
TWD	0.24	CZK	0.25	MXN	0.24	HUF	0.24
SEK	0.25	HUF	0.25	SEK	0.27	PHP	0.25
ZAR	0.28	IDR	0.26	ZAR	0.29	NZD	0.30
HKD	0.29	NZD	0.31	HKD	0.30	MXN	0.34
JPY	0.38	MXN	0.33	JPY	0.40	IDR	0.35

Table A6: HML Factors Correlation Matrix

The table presents the correlation matrix of investment strategies' HML spread portfolios. We consider skewness risk premia (SRP), carry (CAR), net-foreign assets (NFA), risk-reversal (RR), short-, medium-, and long-term momentum (MOMS, MOMM, and MOML, respectively), value (VAL), variance risk premium (VRP), upside variance, downside variance, and asymmetric variance risk premium (VRPU, VRPD, and VRPUD, respectively). See detailed description of the currency strategies in the Internet Appendix (Section III). The sample spans the period from February 1998 to December 2021 at monthly frequency.

	SRP	CAR	NFA	RR	MOMS	MOMM	MOML	VAL	VRP	VRPD	VRPU	VRPUD
SRP	1	0.79	0.73	0.58	-0.11	0.03	0.04	0.36	0.57	0.79	0.72	0.82
CAR	0.79	1	0.81	0.57	-0.18	0.02	0.04	0.42	0.63	0.82	0.70	0.87
NFA	0.73	0.81	1	0.58	-0.29	-0.17	-0.17	0.41	0.63	0.82	0.73	0.87
RR	0.58	0.57	0.58	1	-0.13	-0.10	-0.13	0.30	0.39	0.61	0.57	0.67
MOMS	-0.11	-0.18	-0.29	-0.13	1	0.28	0.25	-0.18	-0.27	-0.25	-0.20	-0.26
MOMM	0.03	0.02	-0.17	-0.10	0.28	1	0.73	-0.36	-0.03	-0.07	-0.09	-0.07
MOML	0.04	0.04	-0.17	-0.13	0.25	0.73	1	-0.39	0.02	-0.05	-0.15	-0.09
VAL	0.36	0.42	0.41	0.30	-0.18	-0.36	-0.39	1	0.38	0.47	0.36	0.46
VRP	0.57	0.63	0.63	0.39	-0.27	-0.03	0.02	0.38	1	0.83	0.31	0.67
VRPD	0.79	0.82	0.82	0.61	-0.25	-0.07	-0.05	0.47	0.83	1	0.62	0.90
VRPU	0.72	0.70	0.73	0.57	-0.20	-0.09	-0.15	0.36	0.31	0.62	1	0.78
VRPUD	0.82	0.87	0.87	0.67	-0.26	-0.07	-0.09	0.46	0.67	0.90	0.78	1

IV. Econometric Methods

We briefly review the standard two-pass and GMM estimators here. We then present the three-pass estimator in detail.

IV.1. Two-pass Inference

As is usual, we posit that the stochastic discount factor (SDF) is a linear function of some risk factors, f_{t+1}

$$m_{t+1} = 1 - b'\big(f_{t+1} - \mu_f\big), \tag{IV.1}$$

where b is a vector of free parameters. The condition of no-arbitrage ensures the existence of a positive SDF such that

$$E[m_{t+1}X_{nt+1}] = 0 \Rightarrow E[X_{nt+1}] = \beta_n'\lambda, \tag{IV.2}$$

where X_{nt} denotes the excess return for portfolio n at time $t+1$, and the factor loadings, $\beta_n \equiv cov(X_{nt}, f_t)var(f_t)^{-1}$, are defined by the regression coefficients in

$$X_{nt} = a_n + \beta_n' f_t + \epsilon_{nt}. \tag{IV.3}$$

Note that the intercept a_n is not necessarily equal to zero when f_t contains nontradable factors.

Based on the estimates of β_n, the factor's risk premium can then be estimated in the cross-sectional regression,

$$E_T[X_{nt}] = \beta_n'\lambda + \alpha_n, \tag{IV.4}$$

where $E_T[\cdot]$ denotes the sample average, and α_n represents the pricing error. When the model is correctly specified, i.e., f_t captures all systematic risk, α_n should be equal to zero.

The above procedure is the well-known Fama-MacBeth two-pass regression (Fama and MacBeth, 1973), which provides us with the estimates of β and λ. For correcting for the facts that β's are estimated and/or that errors may be autocorrelated and heteroskedastic, we compute both Shanken (1992) corrected standard errors and GMM standard errors with the Newey and West (1987) adjustment (see, e.g., Cochrane, 2005).

Furthermore, we also use the generalized method of moments (GMM) of Hansen (1982) to directly estimate the SDF parameter b, with which we can test whether a factor is really needed in the SDF being a *true* pricing factor. The factor risk premium, or market price of risk, parameter λ is connected to the SDF parameter b by $\lambda = \Sigma_F b$, where Σ_F denotes the variance-covariance matrix of the f_t factors. In particular, following Burnside (2011) and Menkhoff et al. (2012a), we construct the following moment conditions,

$$g_T(\theta) = \begin{bmatrix} E_T\big[X\big] - X(f-\mu_f)'b \\ E_T[f] - \mu_f \\ vec\Big(cov(f)\Big) - vec\Big(\Sigma_f\Big) \end{bmatrix}, \tag{IV.5}$$

where X is a $N \times T$ matrix containing all portfolio excess currency returns, f is a $K \times T$ matrix of currency factors, and θ contains all model parameters $(b', \mu_f', vec(\Sigma_f)')'$. Such moment conditions enable us to take into account the fact that both factor means (μ_f)

and covariance (Σ_f) are estimated when computing standard errors of b and λ. Given that the number of test assets in the paper is relatively large, the statistically optimal weighting matrix in GMM suggested by Hansen (1982) may be nearly singular. For this reason, we use a prespecified weighting matrix, which we choose to be the identity matrix. As discussed in Cochrane (2005), the use of the identity matrix in GMM can provide us with more robust estimates.[35]

IV.2. Three-Pass Inference

`The RP-PCA Estimator.` To begin with, we assume that K factors capture the systematic component of asset returns and the unexplained idiosyncratic component subsumes the asset-specific risks, such that

$$X_{nt} = \mathrm{F}_t\psi_n^\top + \epsilon_{nt}, \qquad n = 1,\dots,N, \quad t = 1,\dots,T, \tag{IV.6}$$

where X_{nt} is the n-th test asset's time-t excess return, $F_t = [F_{1t},\dots F_{Kt}]$ denotes the time-t $1 \times K$ vector of latent factors, ψ_n is the $1 \times K$ vector of factor loadings for test asset n, and ϵ_{nt} is the asset return's idiosyncratic component. In matrix notation, it takes the compact form $X = \mathrm{F}\psi^\top + \epsilon$, where X is a $T \times N$ matrix of returns, F is the $T \times K$ matrix of latent factors, ψ is the $N \times K$ matrix of factor loadings, and ϵ is the $T \times N$ matrix of residuals.

The RP-PCA estimator delivers the estimates of the factor loadings (ψ_n) and the latent factors (F_t) by applying standard PCA to the covariance matrix

$$\Sigma_{\mathrm{RP}} = \frac{1}{T}X^\top X + \omega\,\overline{X}^\top\,\overline{X}, \tag{IV.7}$$

where $\overline{X}$ denotes the sample mean of excess returns and ω is the penalty term, or RP-weight. The risk exposures (or factor loadings) are proportional to the eigenvectors associated with the largest eigenvalues of the Σ_{RP} matrix. Factors are then obtained by regressing the test-asset returns on the factor loadings, i.e., $\hat{F} = X\hat{\psi}(\hat{\psi}^\top\hat{\psi})^{-1}$. Note that, using $\omega = -1$, the risk exposures are proportional to the eigenvectors associated with the largest eigenvalues of $\Sigma_{\mathrm{PCA}} = \frac{1}{T}X^\top X - \overline{X}^\top\,\overline{X}$, which are equal to the factor variances. By contrast, the eigenvalues of Σ_{RP} relate to a generalized notion of "signal strength" of a factor, because it also embeds the information in the test assets expected returns.

LP show that the matrix Σ_{RP} should converge to

$$\psi(\Sigma_F + (1+\omega)\mu_F^\top\mu_F)\psi^\top + \mathrm{Var}(\epsilon), \tag{IV.8}$$

where Σ_F and μ_F denote the covariance matrix and the means of F, respectively. Moreover, applying PCA to Σ_{RP} is equivalent to minimizing jointly the time-series unexplained

[35] Cochrane (2005, p.307) argues "at least, in many cases of practical importance, a simple first-stage GMM approach, focusing on economically interpretable moments, can be adequately efficient, robust to model misspecifications, and ultimately more persuasive."

variation and the cross-sectional pricing errors

$$\min_{\psi,F} \underbrace{\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{nt} - F_t\psi_n^\top)^2}_{\text{TS unexplained variation}} + \omega \underbrace{\frac{1}{N}\sum_{i=1}^{N}(\overline{X}_n - \overline{F}\psi_n^\top)^2}_{\text{CS pricing error}}, \tag{IV.9}$$

where $\overline{F}$ is the vector of factor expected values. From Eqs. (IV.7)-(IV.9), it is clear that using $\omega = -1$ forgoes the information in the means.

The three-pass estimator discussed below presumes that the researcher has already estimated the latent factors and determined the associated SDF, in a way that it accurately spans the space of asset returns. In essence, the RP-PCA estimator can help achieve this goal, as it combines two moment conditions in the factor extraction: it selects factors that explain both the time-series comovement and the cross-sectional spreads, but at the same time penalizes factors with low Sharpe ratios (unlike the standard PCA estimator). By doing so, RP-PCA pushes up the factor signal-to-noise ratios, leading to more efficient estimates of the factors. As a result, weak latent factors with high Sharpe ratios should be detected more easily, and the relevant pricing information should be aggregated in a reasonably small set of factors. Thus, the SDF recovered using RP-PCA should accurately span all relevant sources of priced risk.

Evaluation Metrics. A few evaluation metrics can help determine the "optimal" SDF, that is, the RP-PCA penalty ω and the number K of latent pricing factors, to use in the three-pass estimator. A useful metric to look at is the *maximal Sharpe ratio* of the tangency portfolio of the efficient frontier spanned by the estimated latent factors. The tangency portfolio is given by a linear combination of the K selected latent factors, $\hat{F} \times \hat{b}_{MV}^\top$, where $\hat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$ is a $1 \times$ K vector of weights. Because the tangency portfolio is an affine transformation of the SDF, the $\hat{b}_{MV}$ entries also capture the factor weights in the implied SDF, $\varphi_t = 1 - (\hat{F}_t - \mu_F)\hat{b}_{MV}^\top$.

Two additional metrics are the root-mean-square error ($\overline{RMS}_\alpha$), and the magnitude of the idiosyncratic variance ($\overline{\sigma}_\epsilon^2$). To construct such metrics, call-it *first-pass diagnostics*, one can run a battery of OLS regressions

$$X_{nt} = \alpha_n + \hat{F}_t\psi_n^\top + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{IV.10}$$

where the intercept α_n captures the magnitude of the asset-specific pricing errors. Then, one can use Eq. (IV.10) to compute $\overline{RMS}_\alpha = \sqrt{\hat{\alpha}\hat{\alpha}^\top/N}$, and $\overline{\sigma}_\epsilon^2 = \frac{1}{N}\sum_{n=1}^{N}\left[Var(\hat{\epsilon}_n)/Var(X_n)\right]$ implied by $\hat{F}$. For higher values of the penalty, the pricing error should diminish at the cost of higher variance of the idiosyncratic component. Therefore, based on these statistics, one can evaluate the trade-off to select the penalty value, ω. We then complement these metrics with the *second-pass diagnostics*. Specifically, we use the mean absolute errors (MAE) of the cross-sectional regression, $\overline{X}_n = \hat{\psi}_n\gamma^\top + a_n$, for $n = 1, \ldots, N$, where γ is the $1 \times K$ vector of latent factors' prices of risk, and the R-squared values (R^2).

Finally, a further crucial evaluation metric to choose the appropriate number of latent factors is that the resulting SDF must fully span the information in the test asset returns, which means that no alpha is left explained. Therefore, we test the hypothesis that each of the alphas in individual test asset returns is zero to corroborate the choice of the optimal latent-factor SDF. Given the large number of test assets, we are mindful that these tests are afflicted by multiple hypothesis testing bias. However, in our application it will turn out that the model selected on the basis of the evaluation criteria discussed above prices the cross-section of currency portfolio returns very well and no alpha is found to be statistically significantly different from zero, which allays any concern in the choice of the appropriate dimension of the SDF.[36]

`The RP-PCA Three-Pass Estimator.`

1. `Test-Asset Exposures to Latent Factors` (ψ). The first pass of GX consists of estimating test-asset risk exposures to latent factors. The risk exposures are implied in the factor model of Eq. (IV.6) and, hence, are already delivered by RP-PCA. Alternatively, given the factors extracted via RP-PCA, one can recover the exposures via OLS (as GX do in the standard three-pass estimator based on PCA). But to do so one has to first transform the excess return data and the factors such that incorporate the information of their means. Specifically, the time-series OLS regressions become

$$\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{IV.11}$$

where $\tilde{X}_{nt} = X_{nt} + \tilde{\omega}\bar{X}_{nt}$, and the vector $\tilde{F}_t$ contains elements defined as $\tilde{F}_{kt} = \hat{F}_{kt} + \tilde{\omega}\bar{F}_{kt}$ for $k = 1, \ldots, K$, with $\tilde{\omega} = \sqrt{\omega + 1} - 1$. It is evident that using PCA, i.e., $\omega = -1$, the exposures are given by OLS regressions using the original, unadjusted data and factors.

2. `Latent Factor Prices of Risk` (γ). The second pass delivers the estimates of the prices of risk of the latent factors. The estimates are obtained by running a cross-sectional regression of average realized excess returns on the previously estimated exposures of the test assets to the latent factors,

$$\overline{X}_n = \hat{\psi}_n \gamma^\top + a_n, \quad n = 1, \ldots, N, \tag{IV.12}$$

where γ is the $1 \times K$ vector of the latent factor prices of risk.[37]

3. `Candidate Factor Price of Risk` (λ_g). The last pass of the GX procedure yields the risk premium of the candidate factor g_t. First, one projects the candidate factor onto the space of the latent pricing factors, by running a time-series spanning regression of the candidate factor innovation, g_t^ι, on the demeaned latent factors, $\hat{F}_t^\iota = \hat{F}_t - \mu_F$, as follows

$$g_t^\iota = \hat{F}_t^\iota \eta^\top + u_t, \tag{IV.13}$$

where η is the $1 \times K$ vector collecting the loadings of the candidate factor on the K latent

[36]The RP-PCA estimator assumes full spanning, given that the factor model imposes a zero intercept. Nevertheless, standard GRS-type tests cannot be implemented in this setting, because they are derived under different assumptions on N and T. For this reason and to keep the analysis simple, we test for each test asset if its average pricing error is significant. In a multi-hypothesis testing setting, one should expect no more than 5% of test assets (hence three in our case given that $N = 60$) to have significant average pricing errors at the 5% level.

[37]Note that the factors extracted using the RP-PCA method are return-based with unrestricted means. Hence, under no-arbitrage, factor prices of risk equal their means, i.e., $\gamma = \mu_F$. However, the second pass is still useful, as it allows us to evaluate the fit of the latent-factor model and, more importantly, determine the uncertainty around the estimates; indeed, such uncertainty is accounted for in the computation of the asymptotic standard errors of the candidate factors' risk-premium estimates (i.e., step 3 of the three-pass procedure).

factors. Then, using the estimated η-exposures, one implements

$$\hat{\lambda}_g = \hat{\gamma}\hat{\eta}^\top, \tag{IV.14}$$

$$\hat{g}_t = \hat{F}_t\hat{\eta}^\top, \tag{IV.15}$$

and obtains the *price of risk* of the candidate factor, $\hat{\lambda}_g$, and the *de-noised* candidate factor, $\hat{g}_t$. This de-noised factor is a tradable return-based factor, and should be interpreted as the raw candidate factor (either tradable or nontradable) cleaned from measurement error and/or unpriced risk.

V. Optimal SDF, Three-pass Inference, and De-Noised Factors

In this section, we provide additional tables and figures regarding the latent-factor SDF, the three-pass analysis, and de-noised factors. Specifically, in what follows, we present the three-pass risk-premium estimates for nontradable factors, focusing on SRP_{NT}.

`Nontradable factors`. In Section 5, using the two-pass estimator, we have shown that not only the SRP_{HML}, but also its nontradable counterpart, SRP_{NT}, shows an accurate pricing performance despite its nontradable nature. However, despite the evident appeal of working with nontradable factors – as they connect more directly with primitive economic sources of macro-financial risk – the estimation of their risk premia is notoriously cumbersome. A model-free estimate of their risk premium is not readily available, and they are often measured with large errors, which results in a low signal-to-noise ratio (e.g., Nucera, Sarno, and Zinna, 2024). This can in turn distort the two-pass inference, making almost mandatory the use of the three-pass procedure (Giglio and Xiu, 2021), to which we turn next.

Table A9, SRPNT panel, shows the three-pass estimates of SRP_{NT}, using models including up to nine factors (recall that the optimal SDF consists of seven). In this section, we work with standardized nontradable factors, which allows us to make direct comparisons of exposures to risk and risk premia across factors. Most of the variation in SRP_{NT} is explained by F_2, as is also the case for SRP_{HML}. Also the exposure to F_7 is positive and statistically significant, but its contribution in terms of R^2 is tiny. Overall, a large fraction of the variation in SRP_{NT} is unexplained, showing that measurement error is indeed nonnegligible. Importantly, its risk-premium estimate using the seven latent factors is statistically significant at the 5% level. The Sharpe ratio is also reasonably high, being only slightly lower than the tradable factor estimate (0.75 vs. 0.82).

The impact of the pricing factors on de-noised SRP_{NT} can be easily visualized in Figure A6, top left panel, by looking at the de-noised SRP_{NT} for SDFs of different dimension. It is clear that average returns rise as we increase the number of factors in the SDF (up to the seventh), with the only exception of F_5, as was also the case for SRP_{HML}.

We then assess how de-noised nontradable SRP performs in pricing currency portfolios using standard asset pricing tests. Specifically, Table A10 repeats the FMB and GMM analysis of Table A8, by replacing de-noised SRP_{HML} with de-noised SRP_{NT}. The resulting evidence is fairly clearcut. The pricing accuracy remains accurate, regardless of the cross-section of test assets considered. In the largest cross-section (D), for example, the R^2 is 0.84 and the bs of SRP_{NT} and MOMS have t-statistics well above 3.

Taken together, this analysis allows us to rule out that the two-pass analysis results using raw SRP_{NT}, presented in Section 4.2 and refined in Section VI using larger cross-sections of test assets, are due to either measurement error in the factor and/or to the potential omission of relevant control factors in the SDF. Moreover, this additional analysis shows that also the *de-noised* SRP_{NT} and SRP_{HML} factors seem to be closely related, for example yielding similar Sharpe ratios and performing similarly in standard asset pricing tests. This in turn validates our choice to carry out the main asset pricing analysis using the tradable factor SRP_{HML}. More importantly, we can conclude, even more fearfully, that skewness risk (premia) is priced in currency returns.

`Other option-based measures`. To complete the analysis, we present in Table A9 the three-pass risk-premium estimates for some other option-based nontradable factors, which are often used to capture volatility, tail, and uncertainty risks, in the FX and other markets. Specifically, GIV is the option-based counterpart of the global FX volatility measure of Menkhoff et al. (2012a) as it is constructed using currency option implied volatilities for our sample; VXO and MOVE indices are the implied volatilities in the U.S. equity and government bond markets, respectively. Then, EQTAIL is the option-based equity tail factor of Fan, Londono, and Xiao (2022), which is regarded as a measure of global tail risk.[38] While EQTAIL is a return-based measure, because it goes long and short U.S. equity indices, it is not directly tradable in the currency market, and hence we add to the list of nontradable factors.

To begin with, we note that all these factors behave as countercyclical factors, as their risk-premium point estimates are negative, as one would expect. However, none of the risk-premium estimates are statistically significant, based on the optimal seven-factor model. This is in stark contrast with SRP_{NT}, whose risk-premium estimate is strongly significant. Their Sharpe ratios are also substantially lower than the Sharpe ratio of SRP_{NT}. By looking at the cumulative returns of the de-noised nontradable factors (Figure A6), it is also evident the absolute performances of most of these factors vanish post-GFC (possibly with the only exception of the MOVE index).

[38]Fan, Londono, and Xiao (2022) use the equity tail factor to sort currencies dynamically into portfolios via their estimated rolling exposures. By contrast, we work directly with the nontradable tail factor, without converting it first into the HML factor associated with their currency investment strategy, as the latter factor could be exposed to an omitted-variable bias in its construction.

Table A7: Latent Factor and SDF Diagnostics by RP-weight

The table presents latent factor statistics and SDF diagnostics, obtained by implementing the first two steps of the RP-PCA three-pass estimator. We apply the estimator to the $N = 60$ portfolios associated with the 12 currency investment strategies. We report diagnostics for RP-PCA implemented without "overweight" on the means ($\omega = -1$), i.e., standard PCA, and with increasing values of the RP-weight ($\omega = 10$ and 50). We consider SDFs, $\varphi(F_{1-k})$, including an increasing number of latent factors, $k = 1, 2, \ldots, 9$. In *A.I: Factor Statistics, I.a: Factors*, we report the statistics of the orthogonalized factors: the k-th factor's annualized mean ($\mu_{F,k}$); the k-th factor's annualized Sharpe ratio ($SR_{F,k}$); and the k-th factor's weight in the SDF $\varphi_t = 1 - (\hat{F}_t - \mu_F)\hat{b}_{MV}^{\top}$ ($\hat{b}_{MV,k}$). In *A.II: SDF Diagnostics*, we present the SDF diagnostics. Specifically, *II.a: 1P* shows the first-pass diagnostics: the average idiosyncratic variance, $\overline{\sigma}^2_{\epsilon} = \frac{1}{N}\sum_{n=1}^{N}[Var(\hat{\epsilon}_n)/Var(X_n)]$; and the average root-mean-square pricing errors, $\overline{RMS}_{\alpha} = \sqrt{\hat{\alpha}\hat{\alpha}^{\top}/N}$, obtained by estimating $X_{n,t} = \alpha_n + \hat{F}_t\psi_n^{\top} + \epsilon_{n,t}$, for $n = 1..., N$ test assets, and $t = 1..., T$ months. *II.b: 2P* presents the second-pass diagnostics: the mean absolute errors (MAE) of the cross-sectional regression, $\overline{X}_n = \hat{\psi}_n\gamma^{\top} + a_n$, for $n = 1, \ldots, N$, where γ is the $1 \times k$ vector of latent factors' prices of risk; and the R-squared values ($R^2(\%)$). *II.c: mSR* reports the annualized maximal Sharpe ratio (SR) from the tangency portfolio of the mean-variance frontier spanned by the linear combination of the k selected latent factors, $\hat{F} \times \hat{b}_{MV}^{\top}$, where $\hat{b}_{MV}$ is a $1 \times$ k vector with entries $\hat{b}_{MV,k} = \mu_{F,k}/\sigma^2_{F,k}$, with $\mu_{F,k}$ and $\sigma^2_{F,k}$ denoting the k-th factor's mean and variance; ΔSR denotes the difference in SRs between SDFs with k and $k-1$ factors.

	A.I: Factor Statistics				A.II: SDF Diagnostics					
	I.a: Factors				II.a: 1P		II.b: 2P		II.c: mSR	
$\omega = -1$	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\overline{\sigma}^2_{\epsilon}$	$\overline{RMS}_{\alpha}$	MAE	$R^2(\%)$	SR	ΔSR
F_1	12.37	0.22	0.03	$\varphi(F_1)$	20.85	1.17	0.95	42.48	0.22	
F_2	5.55*	0.39	0.23	$\varphi(F_{1-2})$	15.66	0.93	0.77	51.65	0.45	0.23
F_3	3.46*	0.38	0.34	$\varphi(F_{1-3})$	13.47	0.82	0.69	63.29	0.59	0.14
F_4	1.69	0.24	0.28	$\varphi(F_{1-4})$	12.15	0.79	0.66	64.91	0.64	0.05
F_5	1.70	0.27	0.36	$\varphi(F_{1-5})$	11.11	0.76	0.65	67.62	0.69	0.06
F_6	1.97	0.35	0.52	$\varphi(F_{1-6})$	10.29	0.71	0.60	71.31	0.78	0.08
F_7	0.66	0.13	0.22	$\varphi(F_{1-7})$	9.62	0.71	0.60	71.78	0.79	0.01
F_8	2.49***	0.52	0.91	$\varphi(F_{1-8})$	9.02	0.63	0.50	77.72	0.94	0.16
F_9	0.79	0.17	0.31	$\varphi(F_{1-9})$	8.46	0.62	0.48	78.24	0.96	0.02
$\omega = 10$	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\overline{\sigma}^2_{\epsilon}$	$\overline{RMS}_{\alpha}$	MAE	$R^2(\%)$	SR	ΔSR
F_1	12.68	0.23	0.03	$\varphi(F_1)$	20.85	1.17	0.90	58.03	0.23	
F_2	7.05**	0.51	0.31	$\varphi(F_{1-2})$	15.71	0.91	0.59	71.73	0.56	0.33
F_3	4.99**	0.56	0.52	$\varphi(F_{1-3})$	13.53	0.79	0.42	86.01	0.79	0.23
F_4	3.79**	0.56	0.68	$\varphi(F_{1-4})$	12.25	0.73	0.34	92.49	0.97	0.18
F_5	3.76***	0.62	0.85	$\varphi(F_{1-5})$	11.24	0.65	0.24	95.08	1.15	0.18
F_6	3.35***	0.60	0.90	$\varphi(F_{1-6})$	10.41	0.56	0.19	97.26	1.30	0.15
F_7	3.07***	0.62	1.04	$\varphi(F_{1-7})$	9.75	0.45	0.12	98.65	1.44	0.14
F_8	0.95	0.19	0.31	$\varphi(F_{1-8})$	9.09	0.44	0.12	98.74	1.45	0.01
F_9	0.63	0.14	0.25	$\varphi(F_{1-9})$	8.53	0.44	0.12	98.77	1.46	0.01
$\omega = 50$	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\overline{\sigma}^2_{\epsilon}$	$\overline{RMS}_{\alpha}$	MAE	$R^2(\%)$	SR	ΔSR
F_1	13.55	0.25	0.04	$\varphi(F_1)$	20.90	1.18	0.76	85.44	0.25	
F_2	8.74***	0.73	0.50	$\varphi(F_{1-2})$	16.01	0.95	0.22	96.03	0.77	0.52
F_3	6.28***	0.72	0.69	$\varphi(F_{1-3})$	13.75	0.80	0.11	98.90	1.05	0.29
F_4	5.08***	0.77	0.96	$\varphi(F_{1-4})$	12.49	0.65	0.07	99.72	1.30	0.25
F_5	3.38***	0.53	0.69	$\varphi(F_{1-5})$	11.39	0.55	0.05	99.80	1.41	0.10
F_6	2.64**	0.45	0.65	$\varphi(F_{1-6})$	10.49	0.48	0.04	99.88	1.48	0.07
F_7	2.41**	0.47	0.76	$\varphi(F_{1-7})$	9.79	0.39	0.03	99.93	1.55	0.07
F_8	0.59	0.12	0.20	$\varphi(F_{1-8})$	9.13	0.39	0.03	99.93	1.55	0.00
F_9	0.62	0.13	0.24	$\varphi(F_{1-9})$	8.57	0.38	0.03	99.94	1.56	0.01

Table A8: Pricing Currency Portfolios with De-Noised SRP_{HML} by Cross-Sections

The table presents the cross-sectional asset pricing test results for the carry-related ($N = 15$), past-return-related ($N = 20$), and option-based ($N = 25$) cross-sections, and for the entire cross-section consisting of the $N = 60$ portfolios. The SDF consists of the Dollar factor, DOL, and de-noised SRP and MOMS factors. Specifically, we use the following cross-sections of test assets: (A) the 15 portfolios from the CAR, NFA, and RR strategies; (B) the 20 portfolios from the MOMS, MOMM, MOML, and VAL strategies; (C) the 25 portfolios from the VRP, VRPU, VRPD, VPUD, and SRP strategies; (D) the 60 portfolios from pooling together the portfolios in A, B, and C. In each cross-section, we also include the SRP and MOMS factors as additional test assets. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage GMM estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021.

	A. CAR, NFA, RR				B. MOMS, MOMM, MOML, and VAL			
	A.I FMB				B.I FMB			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
λ	1.493	4.732	3.400	12.8	1.445	5.204	2.789	18.8
(NW)	(1.04)	(3.23)	(2.27)	[0.54]	(1.01)	(3.27)	(1.95)	[0.47]
(Sh)	(1.04)	(3.43)	(2.25)		(1.00)	(3.61)	(1.93)	
		RMSE	*Adj* R^2			RMSE	*Adj* R^2	
		0.63	0.84			0.62	0.77	
	A.II GMM				B.II GMM			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
b	-0.001	0.011	0.009	13.0	-0.002	0.012	0.007	20.6
	(-0.36)	(3.45)	(2.67)	[0.53]	(-0.59)	(3.53)	(2.41)	[0.36]
λ	1.493	4.732	3.400		1.445	5.204	2.789	
	(1.05)	(3.41)	(2.28)		(1.02)	(3.58)	(1.96)	
	C. VRP, VRPU, VRPD, VPUD, SRP				D. All 60 Portfolios			
	A.I FMB				B.I FMB			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
λ	1.489	4.602	3.234	22.6	1.474	4.490	3.030	57.8
(NW)	(1.04)	(3.15)	(2.15)	[0.54]	(1.02)	(3.20)	(2.17)	[0.52]
(Sh)	(1.04)	(3.30)	(2.13)		(1.03)	(3.29)	(2.13)	
		RMSE	*Adj* R^2			RMSE	*Adj* R^2	
		0.60	0.85			0.62	0.80	
	A.II GMM				B.II GMM			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
b	-0.001	0.011	0.008	23.2	-0.001	0.011	0.008	61.7
	(-0.33)	(3.29)	(2.50)	[0.51]	(-0.31)	(3.32)	(2.59)	[0.38]
λ	1.488	4.602	3.234		1.474	4.490	3.030	
	(1.05)	(3.29)	(2.16)		(1.04)	(3.28)	(2.18)	

Table A9: Three-Pass Estimates: Nontradable Factors

The table presents the candidate nontradable factor three-pass estimates. Latent factors are extracted by applying rpPCA (with RP-weight $\omega = 20$) to the baseline sample of $N = 60$ portfolios. We report the risk exposures of the candidate factors to each of the latent factors (η_{F_k}). We then consider SDFs including an increasing number of factors, whereby we add factors one by one. Specifically, we report the candidate factor explained variations in percent ($R^2_{F_{1-k}}$); the annualized risk-premium estimates ($\lambda_{F_{1-k}}$); and the Sharpe ratios of the de-noised factors ($sr_{F_{1-k}}$). We compute nontradable factor AR(1) innovations (except for EQTAIL being return-based) and then standardize them, so that also have unit variance, making the estimates more easily comparable across factors. Panel A and B report the SRP and the other option-based nontradable factors, respectively. ***,**,* denote statistical significance of the risk at the 1-, 5- and 10-percent levels, respectively. The statistical significance is based on the Newey-West for the risk exposures, and on the GX formula for the risk premia.

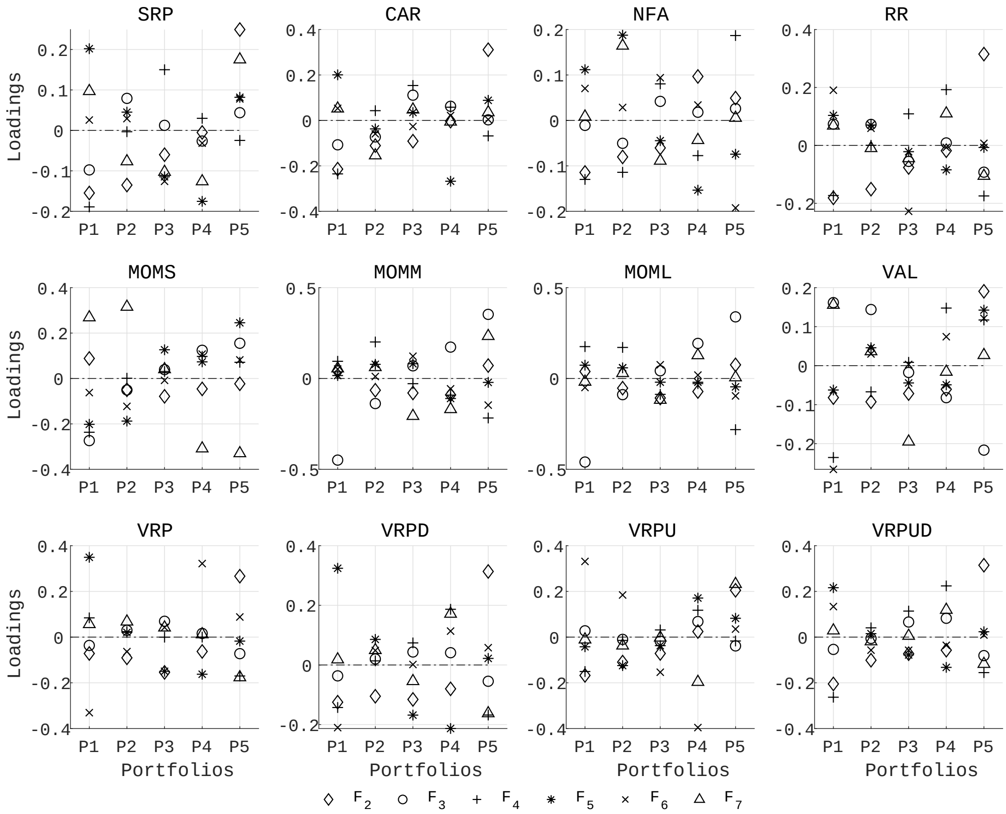
	Panel A: SRP Factor								
k	1	2	3	4	5	6	7	8	9
SRPNT									
η_{F_k}	0.01	0.08***	0.01	0.01	-0.05	0.03	0.09***	-0.01	-0.03
$R^2_{F_{1-k}}$	0.46	8.58	8.29	8.03	8.64	8.61	10.00	9.70	9.59
$\lambda_{F_{1-k}}$	0.07	0.67**	0.72**	0.78**	0.57	0.67*	0.91**	0.90**	0.88**
$SR_{F_{1-k}}$	0.24	0.64	0.68	0.73	0.52	0.60	0.75	0.74	0.72
	Panel B: Other Nontradable Factors								
k	1	2	3	4	5	6	7	8	9
EQTAIL									
η_{F_k}	-0.03***	-0.06***	0.05**	-0.05	0.09	0.15**	-0.07	0.10*	0.05
$R^2_{F_{1-k}}$	17.95	23.16	24.31	24.87	27.20	33.45	34.27	36.18	36.35
$\lambda_{F_{1-k}}$	-0.35	-0.83**	-0.56	-0.79*	-0.45	0.01	-0.18	-0.11	-0.08
$SR_{F_{1-k}}$	0.24	0.49	0.32	0.45	0.24	0.00	0.09	0.05	0.04
GIV									
η_{F_k}	-0.03**	-0.08***	0.02	-0.02	0.11*	0.16	-0.11	-0.00	-0.09
$R^2_{F_{1-k}}$	21.84	31.08	31.19	31.09	34.66	41.72	44.32	44.12	45.57
$\lambda_{F_{1-k}}$	-0.38	-1.02**	-0.89**	-0.98*	-0.57	-0.08	-0.39	-0.39	-0.45
$SR_{F_{1-k}}$	0.24	0.52	0.45	0.50	0.28	0.04	0.17	0.17	0.19
VXO									
η_{F_k}	-0.03***	-0.06***	0.03	-0.07***	0.04	0.07*	-0.06*	0.06*	0.02
$R^2_{F_{1-k}}$	20.96	25.45	25.63	27.25	27.47	28.67	29.08	29.59	29.38
$\lambda_{F_{1-k}}$	-0.38	-0.83**	-0.68*	-1.01**	-0.87*	-0.65	-0.80*	-0.76	-0.75
$SR_{F_{1-k}}$	0.24	0.47	0.38	0.55	0.47	0.34	0.41	0.39	0.38
MOVE									
η_{F_k}	-0.01***	-0.05***	0.01	-0.04	0.07*	0.06	-0.03	-0.01	0.01
$R^2_{F_{1-k}}$	4.52	8.16	7.90	8.05	9.43	10.07	10.01	9.73	9.41
$\lambda_{F_{1-k}}$	-0.18	-0.59**	-0.53	-0.70**	-0.43	-0.25	-0.35	-0.36	-0.35
$SR_{F_{1-k}}$	0.24	0.57	0.52	0.66	0.37	0.21	0.29	0.29	0.29

Table A10: Pricing Currency Portfolios with De-Noised SRP_{NT} by Cross-Sections

The table presents the cross-sectional asset pricing test results for the carry-related ($N = 15$), past-return-related ($N = 20$), and option-based ($N = 25$) cross-sections, and for the entire cross-section consisting of the $N = 60$ portfolios. The SDF consists of the Dollar factor, DOL, and de-noised nontradable SRP (SRP_{NT}) and MOMS factors. Specifically, we use the following cross-sections of test assets: (A) the 15 portfolios from the CAR, NFA, and RR strategies; (B) the 20 portfolios from the MOMS, MOMM, MOML, and VAL strategies; (C) the 25 portfolios from the VRP, VRPU, VRPD, VPUD, and SRP strategies; (D) the 60 portfolios from pooling together the portfolios in A, B, and C. In each cross-section, we also include the SRP and MOMS factors as additional test assets. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage GMM estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021.

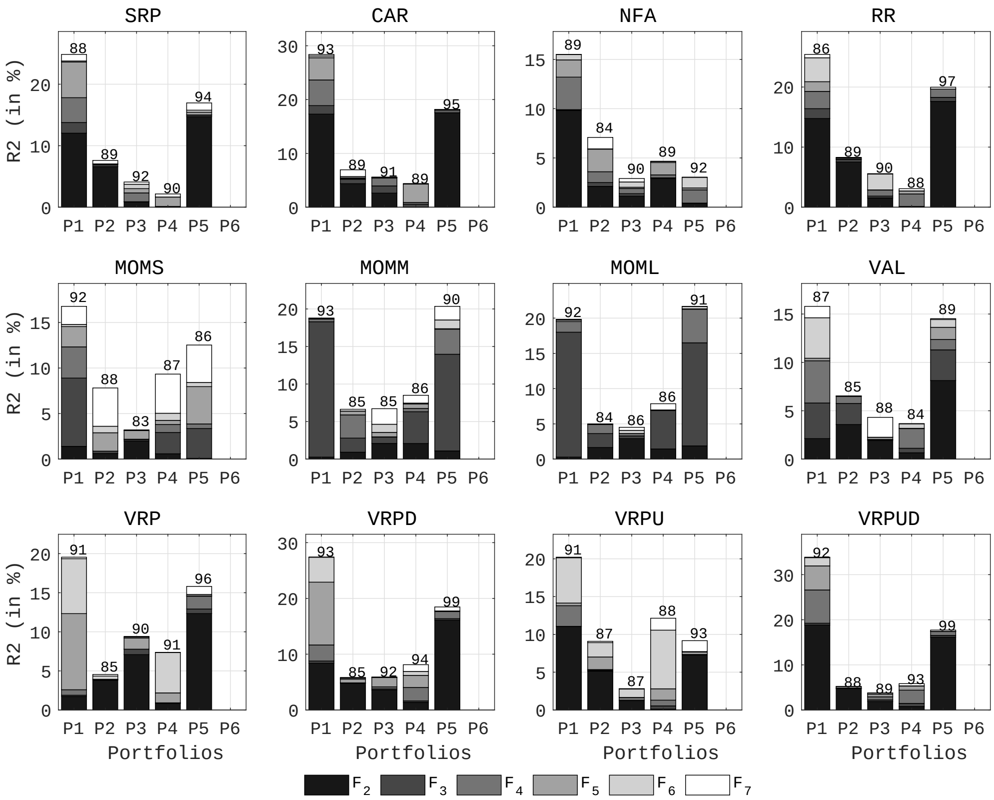
	A. CAR, NFA, RR				B. MOMS, MOMM, MOML, and VAL			
	A.I FMB				B.I FMB			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
λ	1.491	0.701	3.337	10.6	1.450	0.787	2.680	16.3
(NW)	(1.04)	(2.39)	(2.26)	[0.72]	(1.01)	(2.54)	(1.88)	[0.64]
(Sh)	(1.04)	(2.51)	(2.21)		(1.00)	(2.83)	(1.85)	
		RMSE	*Adj* R^2			RMSE	*Adj* R^2	
		0.55	0.88			0.59	0.79	
	A.II GMM				B.II GMM			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
b	0.002	0.065	0.012	10.6	0.002	0.068	0.011	17.3
	(0.68)	(3.53)	(3.65)	[0.72]	(0.55)	(3.64)	(3.51)	[0.57]
λ	1.491	0.701	3.337		1.450	0.786	2.680	
	(1.05)	(2.51)	(2.28)		(1.02)	(2.79)	(1.90)	
	C. VRP, VRPU, VRPD, VPUD, SRP				D. All 60 Portfolios			
	A.I FMB				B.I FMB			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
λ	1.484	0.679	3.332	19.0	1.474	0.678	2.967	52.1
(NW)	(1.03)	(2.35)	(2.23)	[0.75]	(1.02)	(2.43)	(2.13)	[0.73]
(Sh)	(1.03)	(2.45)	(2.19)		(1.03)	(2.48)	(2.08)	
		RMSE	*Adj* R^2			RMSE	*Adj* R^2	
		0.50	0.89			0.56	0.84	
	A.II GMM				B.II GMM			
	DOL	SRP	MOMS	χ^2	DOL	SRP	MOMS	χ^2
b	0.002	0.064	0.012	20.3	0.002	0.062	0.011	57.3
	(0.70)	(3.42)	(3.54)	[0.68]	(0.67)	(3.47)	(3.64)	[0.54]
λ	1.484	0.679	3.332		1.474	0.678	2.967	
	(1.04)	(2.44)	(2.25)		(1.04)	(2.48)	(2.14)	

Figure A2: Portfolio Risk Exposures to Latent Factors



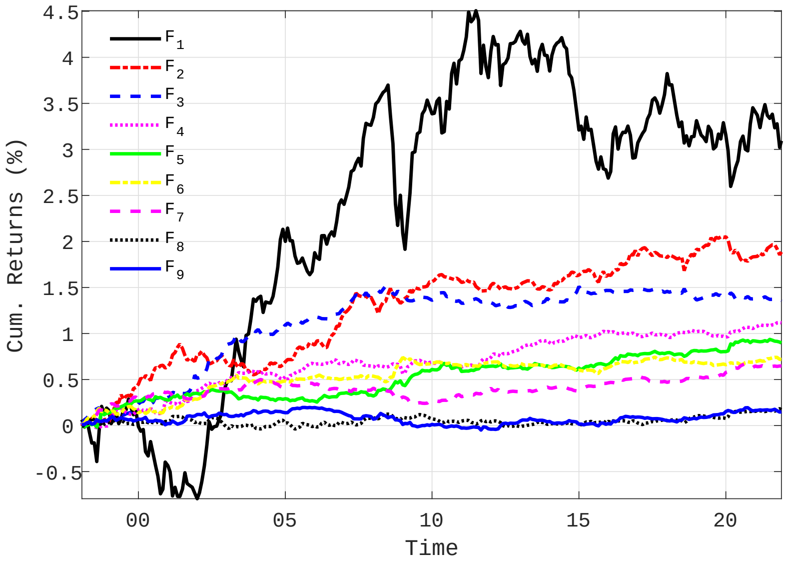
The figure shows portfolio loadings on the estimated latent factors from the panel of currency portfolios excess returns by means of RP-PCA with baseline RP-weight, i.e., $\omega = 20$. We omit to report exposures to the first factor, to better visualize the evidence of the remaining factors. The RP-PCA factor loadings can also be obtained through OLS regressions using transformed data that incorporate the cross-sectional error. Specifically, define $\tilde{\omega}_{nt} = \sqrt{\omega + 1} - 1$, $\tilde{X}_{nt} = X_{nt} + \tilde{\omega}\bar{X}_{nt}$ and $\tilde{F}_{kt} = \hat{F}_{kt} + \tilde{\omega}\bar{F}_{kt}$. Then, for any value of ω, RP-PCA loadings are given by the coefficients $(\tilde{\psi}_n)$ from the OLS time-series regressions, $\tilde{X}_{n,t} = \tilde{F}_t\tilde{\psi}_n^\top + \tilde{e}_{n,t}$, $n = 1, \ldots, N$, $t = 1, \ldots, T$. The test assets' sample consists of the $N = 60$ portfolios associated with the nine investment strategies. The sample spans the 2/1998-12/2021 period at monthly frequency ($T = 287$).

Figure A3: Portfolio Explained Variations by Latent Factors



The figure shows the R^2s obtained by regressing currency portfolios' excess returns (X_{nt}) on the first seven estimated orthogonalized latent factors ($\hat{F}_t = [\hat{F}_{1t}, \ldots, \hat{F}_{kt}]$, with $k = 7$). Factors are estimated from the panel of test asset excess returns by means of RP-PCA with baseline RP-weight (i.e., $\omega = 20$). The estimated factors are then orthogonalized, to facilitate their economic interpretation. We estimate $N \times K$ OLS time-series regressions, $X_{nt} = \alpha_n + \hat{F}_{1:kt}\psi_n^\top + e_{nt}$, $n = 1, \ldots, N$, $t = 1, \ldots, T$, $k = 1, \ldots, K$, with $\hat{F}_{1:kt} = [\hat{F}_{1t}, \ldots, \hat{F}_{kt}]$. For each portfolio, we show factor contributions to the overall portfolio R_n^2. We omit to report the contribution of $\hat{F}_{1t}$, to better visualize the evidence of the remaining factors. We show the five-factor model R_n^2s above the bars. The test assets' sample consists of the $N = 60$ portfolio excess returns associated with the 12 investment strategies. The sample spans the 2/1998-12/2021 period at monthly frequency ($T = 287$).

Figure A4: Latent Factors



The figure shows the cumulative returns of the first nine estimated, orthogonalized latent factors. The sample spans the 2/1998-12/2021 period at monthly frequency ($T = 287$).

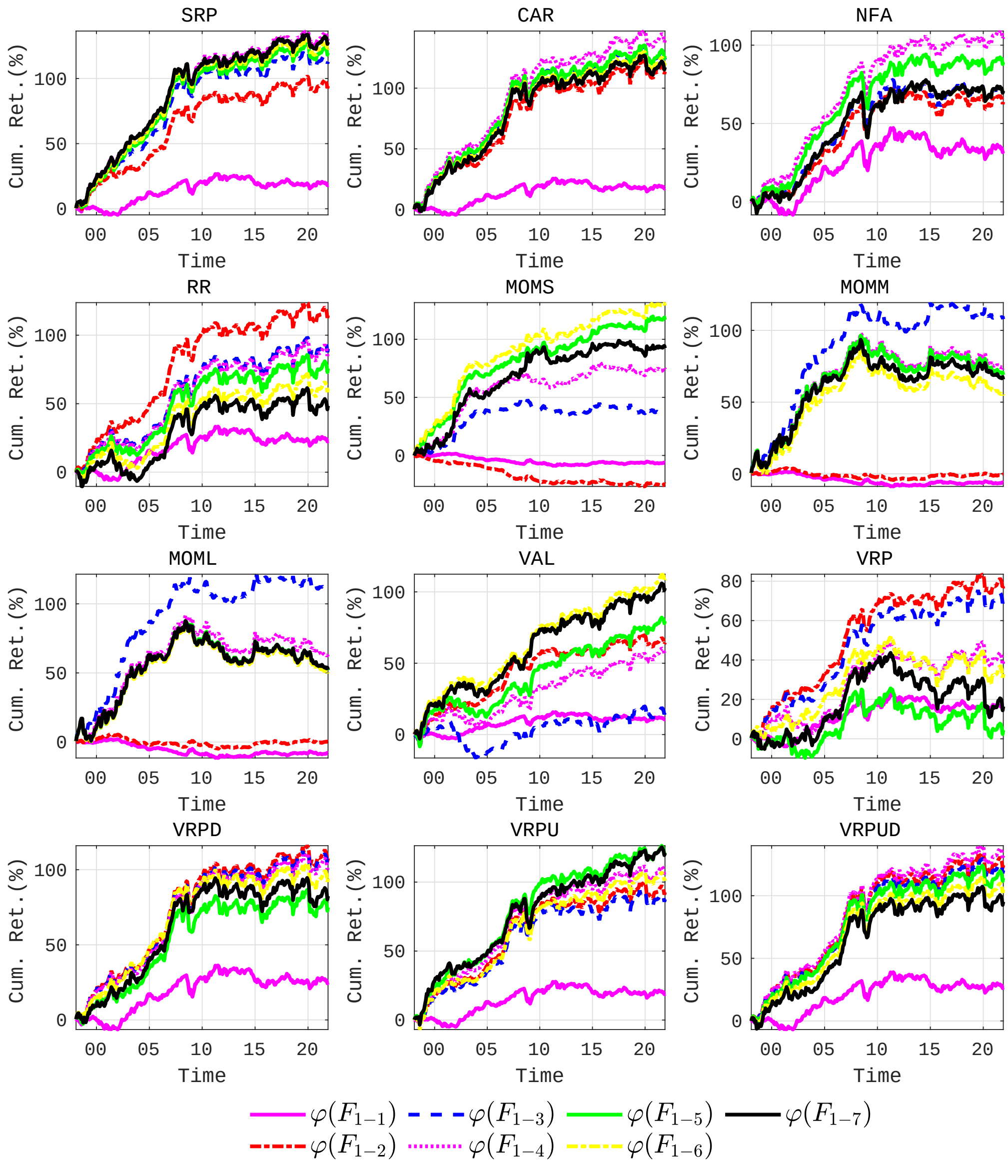
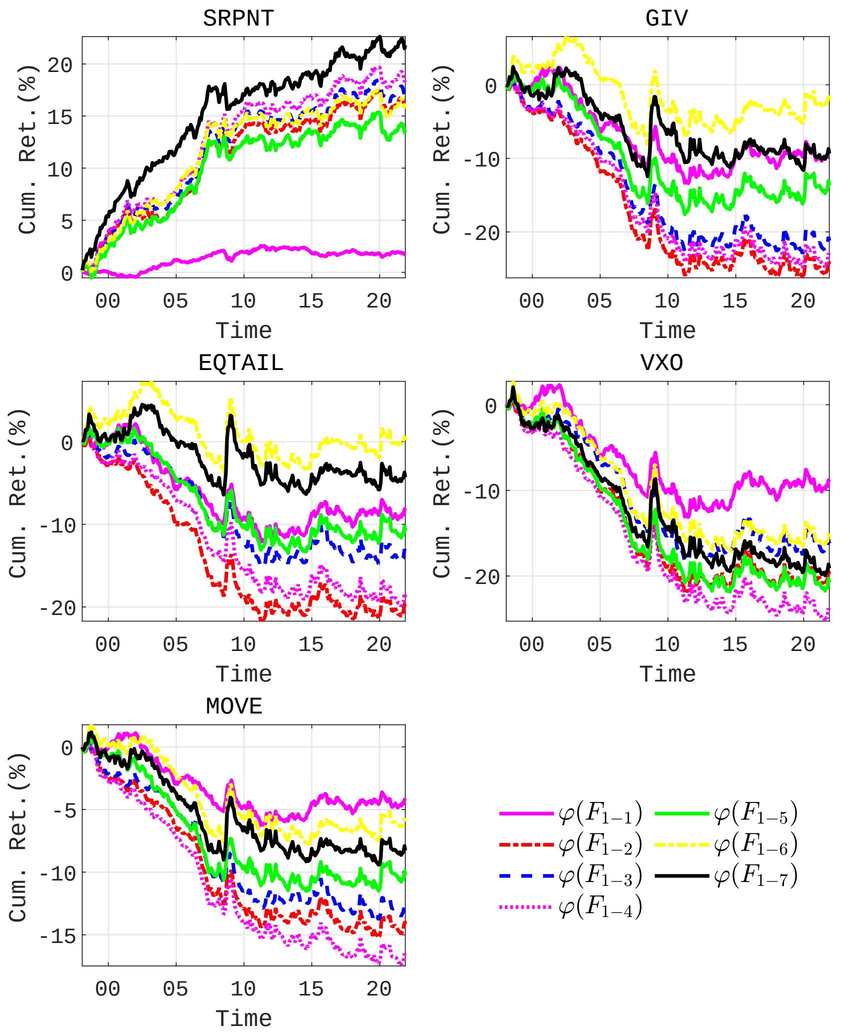


Figure A5: De-noised HML Factors by SDFs

The figure shows the de-noised HML factors associated with the 12 currency investment strategies. To de-noise the factors, we use the RP-PCA three-pass model with baseline RP-weight $\omega = 20$ estimated on the $N = 60$ portfolio excess returns associated with the 12 investment strategies. For each HML factor, we present de-noised versions by expanding the dimension of the factor model up to including seven factors, i.e., $\varphi(F_{1-k})$ with $k = 1, 2, \ldots, 7$. Specifically, for $\varphi(F_{1-k})$, the de-noised factor is given by $\hat{F}_t \hat{\eta}^\top$. The sample spans the period from February 1998 to December 2021 period at monthly frequency.

Figure A6: De-noised Selected Nontradable Factors by SDF Dimension



The figure shows the de-noised nontradable factors. To de-noise the candidate factors, we use the RP-PCA three-pass model with baseline RP-weight $\omega = 20$ estimated on the $N = 60$ portfolio excess returns associated with the 12 investment strategies. For each factor, we present $K = 7$ de-noised versions by expanding the dimension of the SDF, i.e., $\varphi(F_{1-k})$ with $k = 1, 2, \ldots, K$. Specifically, for $\varphi(F_{1-k})$, the de-noised factor is given by $\hat{F}_{1:kt}\hat{\eta}^{\top}$. The sample spans the 2/1998-12/2021 period at monthly frequency ($T = 287$).

VI. Asset Pricing Tests with Raw Factors

`Two-factor SDF (DOL and SRP.)` Table A11 presents the asset pricing analysis for the two-factor tradable SDF, including the DOL and SRP_{HML} factors.

In Panel A, we take as test assets the portfolios from CAR, NFA, and RR ($N = 15$).[39] The FMB analysis shows that the SRP_{HML} risk-premium estimate is about 5.01%, which is very close to its sample average (Panel A.I). The cross-sectional adjusted R^2 is about 0.77, and the χ^2 test has a p-value of 0.09. Thus, we cannot reject the null of zero pricing errors at the 5% level. Turning to the GMM estimates (Panel A.II), b_{SRP} is about 0.01 with a t-statistic of 2.70, the risk-premium estimate of SRP_{HML} is precisely estimated, and the p-value of the χ^2 test is also 0.09.

In Panel B, we consider the portfolios from the strategies based on past returns, thus MOMS, MOMM, MOML, and VAL ($N = 20$). We find from the FMB regression that the SRP risk-premium estimate is about 5.32%, which is again highly statistically significant and not different from its sample average (Panel B.I). The cross-sectional adjusted R^2 is about 0.45 and yet the χ^2 test suggests that all alphas are statistically insignificantly different from zero (p-value = 0.14). According to the GMM estimates, the SDF parameter b_{SRP} is about 0.01 with a t-statistic about 2.90, and the χ^2 test fails to reject the null of zero pricing errors (Panel B.II).

In Panel C, we study the five option-based risk-premium strategies, namely VRP, VRPD, VRPU, VRPUD, and SRP ($N = 25$). The evidence is largely in line with that uncovered above for the other two cross-sections. In fact, SRP_{HML} enters the SDF and the pricing errors are statistically jointly equal to zero. The only main difference regards the estimate of the SRP_{HML} risk premium, which is somewhat lower, but remains statistically equal to the SRP_{HML} sample average return.

Finally, in Panel D, we pool together all test assets, so that the cross-section consists of $N = 60$ portfolios (plus the usual SRP_{HML} factor). This cross-section is therefore much larger and hence raises the bar for the asset pricing tests, especially because we rely on a parsimonious two-factor model. Nevertheless, the evidence is largely consistent with the previous evidence resting on smaller cross-sections. The risk-premium estimate of SRP_{HML} is about 4.80%, which remains statistically significant at the 1% level and close to the factor sample average. The cross-sectional adjusted R^2 is 0.67 and the χ^2 test has a p-value of 0.16 using FMB (Panel D.I) and of 0.15 using GMM (Panel D.II). Moreover, the estimate of b_{SRP} is fairly stable (around 0.008) and is statistically significant with a t-statistic of 2.49.

We then examine how the two-factor model performs when we replace the SRP_{HML} factor with the nontradable factor, SRP_{NT}. Table A12 in the Internet Appendix implements the same empirical tests as those of Table A11 using the same four cross-sections of test assets. We find that the model with the SRP nontradable factor also performs quite well no matter which test assets are under consideration: the risk-premium estimate of the SRP nontradable factor is statistically significant; the GMM estimate of b_{SRP} is also statistically significant; and both the FMB and GMM χ^2 tests suggests that all alphas are statistically insignificantly different from zero at the significance level of 5%. Not surprisignly, we find that based on these two-factor models, the model with the tradable

[39] As before, we include the SRP_{HML} factor as an additional test asset in each of the cross-sections considered.

SRP_{HML} factor performs better than that with the nontradable SRP_{NT} factor, for example in terms of standard goodness of fit measures. However, the model including SRP_{NT} performs rather well given that is a nontradable factor.

Overall, we can conclude that, despite the relatively large cross-sections, the two-factor model with DOL and SRP_{HML} performs rather well as the pricing errors are small and the model fit is accurate. Moreover, we find that the SRP_{HML} has a highly statistically significant risk premium (which is close to the factor sample mean) and that it is priced in various cross-sections of assets. At the same time, by looking at the momentum (Panel B) and full (Panel D) cross sections, it is clear that the model fits less well for momentum portfolios. This is conceivable because a two-factor model is a rather parsimonious model to price such large cross-sections, so that the SDF could omit other relevant factors. Next we address this issue by pricing the cross-section of 60 test assets with larger pricing models.

`Three-factor SDF (DOL, SRP and MOMS.)` Table A13, Panel A presents the results from using the SRP_{HML} factor, together with DOL and MOMS. The test assets consist of the 60 portfolios (plus the SRP and MOMS HML factors to ensure that the factor risk-premium estimates are close to their respective factor sample averages). We find that the FMB regression delivers an estimate of the SRP_{HML} factor of about 5.33%, which is highly statistically significant and not different from the factor's sample average. The risk-premium estimate of the MOMS factor is about 3.23%, which is also statistically significant and not different from the MOMS sample average. The cross-sectional adjusted R^2 is about 0.77, which is roughly 10% higher than that based on the previous two-factor model (Panel D, Table A11). Furthermore, the GMM estimate of b_{SRP} is about 0.009 with a t-statistics of 3.05, and the estimate of b_{MOMS} is about 0.006 with a t-statistic of 2.38. The χ^2 tests show that we cannot reject the null that all alphas are jointly statistically equal to zero (the FMB and GMM p-values are 0.28 and 0.20, respectively). Panel B uses the nontradable SRP factor, together with DOL and MOMS. We find that both SRP_{NT} and MOMS are pricing factors in the SDF, and we cannot reject the null of zero pricing errors. The model performance improves relative to the two-factor model (Table A12, Panel D). Therefore, this analysis suggests that there are sizable improvements in moving from the two-factor model to the three-factor model, featuring MOMS in addition to DOL and SRP.

`Four-factor SDFs (DOL, SRP and CAR/VAL.)` Having established that MOMS should also enter the SDF, in Table A14 of the Internet Appendix, we carry out further analysis, by moving to four-factor models which include either the CAR (Panel A) or VAL (Panel B) factors.[40] We find that neither of these factors contain extra pricing information beyond SRP_{HML} (or SRP_{NT}) and MOMS. Moreover, we show that, when we replace SRP_{HML} with CAR in the SDF, the b_{CAR} estimate obtained by GMM is statistically significant and hence CAR enters the SDF (Panel C).

[40]Given that SRP and CAR are highly correlated factors, we add to the SDF the orthogonal component of CAR with respect to SRP_{HML}, i.e. CAR^o, to mitigate multicollinearity problems.

Table A11: Pricing Currency Portfolios with the Tradable SRP Factor

The table presents the cross-sectional asset pricing test results for the carry-related ($N = 15$), past-return-related ($N = 20$), and option-based ($N = 25$) cross-sections, and for the entire cross-section consisting of the $N = 60$ portfolios. The SDF consists of the Dollar factor, DOL, and the tradable SRP factor, SRP_{HML}. Specifically, we use the following cross-sections of test assets: (A) the 15 portfolios from the CAR, NFA, and RR strategies; (B) the 20 portfolios from the MOMS, MOMM, MOML, and VAL strategies; (C) the 25 portfolios from the VRP, VRPU, VRPD, VPUD, and SRP strategies; (D) the 60 portfolios from pooling together the portfolios in A, B, and C. In each cross-section, we also include the SRP_{HML} factor as additional test asset. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage GMM estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021.

A. CAR, NFA, RR				B. MOMS, MOMM, MOML, VAL			
A.I FMB				B.I FMB			
FMB	DOL	SRP_{HML}	χ^2	FMB	DOL	SRP_{HML}	χ^2
λ	1.500	5.006	21.6	λ	1.422	5.318	25.7
(NW)	(1.04)	(2.96)	[0.09]	(NW)	(0.98)	(3.06)	[0.14]
(Sh)	(1.04)	(3.16)		(Sh)	(0.99)	(3.43)	
	RMSE	*Adj* R^2			RMSE	*Adj* R^2	
	0.79	0.77			0.98	0.45	
A.II GMM				B.II GMM			
GMM	DOL	SRP_{HML}	χ^2	GMM	DOL	SRP_{HML}	χ^2
b	-0.001	0.008	21.5	b	-0.001	0.009	26.8
	(-0.36)	(2.70)	[0.09]		(-0.50)	(2.90)	[0.11]
λ	1.500	5.006		λ	1.422	5.318	
	(1.06)	(3.21)			(1.00)	(3.46)	
C. VRP, VRPD, VRPU, VRPUD, SRP				D. All 60 Portfolios			
C.I FMB				D.I FMB			
FMB	DOL	SRP_{HML}	χ^2	FMB	DOL	SRP_{HML}	χ^2
λ	1.494	4.898	24.3	λ	1.472	4.798	69.6
(NW)	(1.04)	(2.95)	[0.44]	(NW)	(1.02)	(2.83)	[0.16]
(Sh)	(1.04)	(3.09)		(Sh)	(1.02)	(2.93)	
	RMSE	*Adj* R^2			RMSE	*Adj* R^2	
	0.60	0.85			0.80	0.67	
C.II GMM				D.II GMM			
GMM	DOL	SRP_{HML}	χ^2	GMM	DOL	SRP_{HML}	χ^2
b	-0.001	0.008	24.3	b	-0.001	0.008	70.4
	(-0.33)	(2.63)	[0.44]		(-0.32)	(2.49)	[0.15]
λ	1.494	4.898		λ	1.472	4.798	
	(1.05)	(3.14)			(1.04)	(2.96)	

Table A12: Pricing Currency Portfolios with the SRP Nontradable Factor

The table presents the results of the cross-sectional asset pricing tests for the carry-related ($N = 15$), past-return ($N = 20$), and option-based ($N = 25$) strategy cross-sections, and for the entire cross-section consisting of the $N = 60$ portfolios. The SDF consists of the Dollar factor, DOL, and the *nontradable* SRP factor, SRP_{NT}. Specifically, we use the following cross-sections of test assets: (A) the 15 portfolios from the CAR, NFA, and RR strategies; (B) the 20 portfolios from the MOMS, MOMM, MOML, and VAL strategies; (C) the 25 portfolios from the VRP, VRPU, VRPD, VPUD, and SRP strategies; (D) the 60 portfolios from pooling together the portfolios in A, B, and C. In each cross-section, we also include the SRP_{HML} factor. We report the factor risk premia, λ, estimated using either the cross-sectional step of the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage of the generalized method of moment (GMM) estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021 at a monthly frequency.

A. CAR, NFA, RR

A.I FMB			
FMB	DOL	SRP_{NT}	χ^2
λ	1.485	2.190	19.3
(NW)	(1.03)	(2.42)	[0.15]
(Sh)	(1.03)	(2.68)	
	RMSE	*Adj* R^2	
	0.82	0.76	
A.II GMM			
GMM	DOL	SRP_{NT}	χ^2
b	0.001	0.139	19.3
	(0.25)	(2.55)	[0.15]
λ	1.485	2.190	
	(1.04)	(2.54)	

B. MOMS, MOMM, MOML, VAL

B.I FMB			
FMB	DOL	SRP_{NT}	χ^2
λ	1.444	1.801	25.6
(NW)	(1.00)	(2.26)	[0.14]
(Sh)	(1.00)	(2.66)	
	RMSE	*Adj* R^2	
	1.15	0.25	
B.II GMM			
GMM	DOL	SRP_{NT}	χ^2
b	0.001	0.114	25.8
	(0.35)	(2.41)	[0.14]
λ	1.444	1.801	
	(1.01)	(2.44)	

C. VRP, VRPD, VRPU, VRPUD, SRP

C.I FMB			
FMB	DOL	SRP_{NT}	χ^2
λ	1.492	2.061	29.3
(NW)	(1.04)	(2.34)	[0.21]
(Sh)	(1.04)	(2.58)	
	RMSE	*Adj* R^2	
	0.70	0.80	
C.II GMM			
GMM	DOL	SRP_{NT}	χ^2
b	0.001	0.131	28.3
	(0.30)	(2.43)	[0.25]
λ	1.492	2.061	
	(1.04)	(2.42)	

D. All 60 Portfolios

D.I FMB			
FMB	DOL	SRP_{NT}	χ^2
λ	1.478	1.825	73.7
(NW)	(1.03)	(2.22)	[0.09]
(Sh)	(1.03)	(2.42)	
	RMSE	*Adj* R^2	
	0.90	0.59	
D.II GMM			
GMM	DOL	SRP_{NT}	χ^2
b	0.001	0.116	72.5
	(0.36)	(2.72)	[0.11]
λ	1.478	1.825	
	(1.03)	(2.28)	

Table A13: Pricing Currency Portfolios with SRP and MOMS Factors

The table presents the cross-sectional asset pricing test results using three-factor stochastic discount factors (SDFs) and the $N = 60$ portfolios associated with the 12 investment strategies. Specifically, the SDF consists of the Dollar factor, DOL, the SRP factor (the tradable factor, SRP_{HML}, in Panel A, and the nontradable factor, SRP_{NT}, in Panel B), and the short-term momentum HML factor, MOMS. The test assets include all 55 portfolios, plus the SRP and MOMS HML factors. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator (top panels) or the first-stage GMM estimator (bottom panels). In the FMB panels, we also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). In the GMM panels, we also present the GMM estimates of the factor weights in the SDF, b. For the FMB regressions, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for the GMM estimations, we report the Newey-West t-statistics in brackets. For both estimators, we also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021.

	A. Tradable SRP Factor					B. Nontradable SRP Factor			
	A.I FMB					B.I FMB			
	DOL	SRP_{HML}	MOMS	χ^2		DOL	SRP_{NT}	MOMS	χ^2
λ	1.479	5.332	3.227	64.9	λ	1.476	2.361	3.213	64.9
(NW)	(1.03)	(3.21)	(2.05)	[0.28]	(NW)	(1.02)	(2.74)	(2.01)	[0.28]
(Sh)	(1.03)	(3.30)	(2.02)		(Sh)	(1.03)	(2.86)	(1.98)	
		RMSE	*Adj* R^2				RMSE	*Adj* R^2	
		0.66	0.77				0.68	0.76	
	A.II GMM					B.II GMM			
	DOL	SRP_{HML}	MOMS	χ^2		DOL	SRP_{NT}	MOMS	χ^2
b	-0.001	0.009	0.006	67.8	b	0.002	0.156	0.008	64.1
	(-0.23)	(3.05)	(2.38)	[0.20]		(0.56)	(2.94)	(3.02)	[0.30]
λ	1.479	5.332	3.227		λ	1.475	2.361	3.203	
	(1.04)	(3.36)	(2.04)			(1.03)	(2.81)	(2.01)	

Table A14: Pricing Currency Portfolios with Alternative SDFs

The table presents the results of the cross-sectional asset pricing tests using alternative, larger SDFs. To begin with, we use a four-factor SDF, consisting of the Dollar factor (DOL), the SRP factor (the SRP_{HML} tradable factor in left panels, and the SRP_{NT} nontradable factor in right panels), the short-term momentum factor (MOMS), and an additional factor. Specifically, in Panel A we use the carry factor, orthogonalized by the SRP factor (CAR^o), whereas in Panel B we use the value factor (VAL). In Panel C, we use a a four-factor SDF but replace the SRP_{HML} with CAR. The test assets consists of the 60 portfolios from the 12 investment strategies, plus the SRP_{HML} as the test assets. We report the factor risk premia, λ, estimated using either the Fama-MacBeth (FMB) two-pass estimator or the first-stage of the generalized method of moment (GMM) estimator. We also report the root-mean-square errors (RMSE) and the cross-sectional adjusted R^2s (Adj. R^2). We also present the GMM estimates of the factor weights in the SDF, b. For FMB, we present t-statistics based on both the Newey-West (NW) and Shanken (Sh) corrected standard errors; for GMM, we report the Newey-West t-statistics in brackets. We also report the pricing-error χ^2 tests, and the corresponding p-values in square brackets. The sample period is from February 1998 to December 2021 at a monthly frequency.

Panel A: Adding the Carry Factor

Panel A.I: Tradable (SRP_{HML})					Panel A.II: Nontradable (SRP_{NT})				
FMB	DOL	SRP_{HML}	MOM	CAR^o	FMB	DOL	SRP_{NT}	MOM	CAR^o
λ	1.478	5.251	3.527	-0.218	λ	1.474	2.291	3.540	0.046
(NW)	(1.03)	(3.24)	(1.96)	(-0.18)	(NW)	(1.02)	(2.94)	(1.90)	(0.04)
(Sh)	(1.03)	(3.47)	(1.94)	(-0.17)	(Sh)	(1.03)	(3.12)	(1.87)	(0.03)
	RMSE	*Adj* R^2	χ^2			RMSE	*Adj* R^2	χ^2	
	0.67	0.77	65.3 [0.21]			0.68	0.75	64.7 [0.23]	
GMM	DOL	SRP_{HML}	MOM	CAR^o	GMM	DOL	SRP_{NT}	MOM	CAR^o
b	-0.001	0.009	0.006	0.001	b	0.002	0.152	0.009	0.002
	(-0.19)	(3.22)	(2.29)	(0.22)		(0.60)	(3.25)	(2.77)	(0.32)
λ	1.478	5.251	3.527	-0.218	λ	1.474	2.291	3.540	0.046
	(1.04)	(3.52)	(1.96)	(-0.18)		(1.03)	(3.11)	(1.90)	(0.404)
		χ^2					χ^2		
		67.1 [0.17]					64.0 [0.24]		

Panel B: Adding the Value Factor

Panel B.I: Tradable (SRP_{HML})					Panel B.II: Nontradable (SRP_{NT})				
FMB	DOL	SRP_{HML}	MOM	VAL	FMB	DOL	SRP_{NT}	MOM	VAL
λ	1.478	5.250	3.828	2.317	λ	1.474	2.159	3.943	3.012
(NW)	(1.03)	(3.19)	(2.34)	(1.23)	(NW)	(1.02)	(2.73)	(2.39)	(1.50)
(Sh)	(1.03)	(3.28)	(2.30)	(1.25)	(Sh)	(1.03)	(2.67)	(2.32)	(1.54)
	RMSE	*Adj* R^2	χ^2			RMSE	*Adj* R^2	χ^2	
	0.66	0.77	63.0 [0.27]			0.67	0.77	63.8 [0.25]	
GMM	DOL	SRP_{HML}	MOM	VAL	GMM	DOL	SRP_{NT}	MOM	VAL
b	-0.001	0.009	0.007	0.001	b	0.002	0.142	0.009	0.002
	(-0.21)	(2.82)	(2.70)	(0.52)		(0.52)	(2.87)	(3.35)	(0.67)
λ	1.478	5.250	3.828	2.316	λ	1.474	2.159	3.943	3.012
	(1.04)	(3.35)	(2.34)	(1.26)		(1.03)	(2.81)	(2.39)	(1.52)
		χ^2					χ^2		
		65.3 [0.21]					63.7 [0.25]		

Panel C: Replacing SRP_{HML} by CAR

FMB	DOL	CAR	MOM	VAL	GMM	DOL	CAR	MOM	VAL
λ	1.476	5.279	3.847	2.263	b	0.000	0.007	0.007	0.001
(NW)	(1.03)	(3.04)	(2.31)	(1.19)		(0.14)	(2.78)	(2.92)	(0.35)
(Sh)	(1.03)	(3.05)	(2.31)	(1.22)	λ	1.476	5.279	3.847	2.263
						(1.05)	(3.05)	(2.32)	(1.22)
	RMSE	*Adj* R^2	χ^2				χ^2		
	0.69	0.76	64.4 [0.23]				65.0 [0.22]		