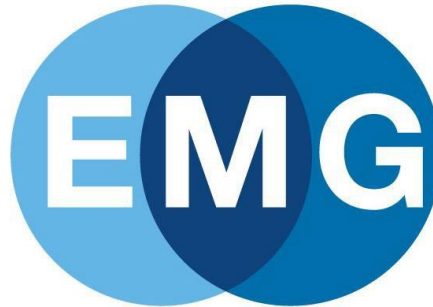




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**‘Skewness Risk Premia and the Cross-
Section of Currency Returns’**

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

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Abstract

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. A tradable SRP factor enters the currency pricing kernel and is central to the pricing of risks inherent in many currency strategies. This evidence emerges using broad cross-sections of portfolio excess returns, employing both conventional and more recent asset pricing tests – which control for omitted variables and measurement errors – and also using a nontradable SRP factor. The results taken together show 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 recent 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 (2020) 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

¹Asset 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 (2022) provide evidence that asset prices might only slowly incorporate objective disaster risk.

embed predictive information for the cross-section of currency portfolio excess returns? Second, is skewness risk priced in the currency market?

While disaster/skewness risk is notoriously hard to measure due to its intrinsic nature of being rare (e.g., Baron, Xiong, and Ye, 2022), out-of-the-money options embed highly valuable 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 refer to the wedge between the two measures as the skewness risk premium (SRP), consistent with the above literature.²

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 measure 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

²In 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, and hence asymmetry in the semivariances is an adequate measure for our purpose.

fluctuations.³

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}), which 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.

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-return, value, and option-based signals), 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.

To begin with, we resort to the standard two-pass method and show that SRP_{HML} enters the currency pricing kernel, or stochastic discount factor (SDF), and is central to the pricing of currency risk, regardless of the specific cross-section of test assets used. In fact, even using a rather parsimonious two-factor model, whereby the SDF includes the Dollar factor and the SRP_{HML} factor, the pricing of currency portfolios is already very accurate (especially for carry-related and option-based cross-sections). By adding to the SDF the short-term momentum factor, the model's pricing performance improves

³In 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.

further; based on the standard pricing-error test (GRS test, Gibbons, Ross, and Shanken, 1989), we fail to reject the null hypothesis that the pricing errors are jointly zero also in the largest cross-section considered, which includes a total of 55 portfolios constructed from 11 currency investment strategies. These 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 connect more directly with primitive economic sources of macro-financial risk.

To limit concerns on the validity of the asset pricing tests, relating to the dimension and selection of the cross-sections of test assets (Lewellen et al., 2010), the analysis discussed so far relies both on a large cross-section and on several smaller cross-sections to better connect SRP_{HML} with various currency strategies. However, to corroborate some of these findings, we also recur to simple factor spanning regressions that help us discern the *true* tradable pricing factors from the subsumed ones without relying on specific choices of test assets (e.g., Barillas and Shanken, 2017). We find that the currency SDF should feature either the SRP_{HML} or the carry factor, and the short-term momentum factor. This is because SRP_{HML} does not price entirely short-term momentum, but it is not subsumed by any of the other 11 tradable HML factors, except carry. Indeed, SRP_{HML} and the carry factor appear to mutually explain each other. Nevertheless, the analysis also shows that SRP_{HML} performs better in pricing carry (than the other way around) and the other strategies. For this reason, we argue that one should prefer the skewness factor over the carry factor in the SDF (of course conditional on having access to option data). In essence, the results from the spanning regressions confirm, but also strengthen, the earlier two-pass evidence.

To complete the analysis, we then recur to the recently developed three-pass asset pricing method, which delivers robust estimates of factor risk premia, accounting for omitted-variable and measurement-error biases. Both sources of bias are likely to be relevant in the two-pass risk-premium estimation, especially when the candidate factor is nontradable. This novel estimator, recently employed by Nucera, Sarno, and Zinna (2023) to achieve robust estimates of currency risk premia, combines the original three-

pass estimator developed by Giglio and Xiu (2021) with the risk-premium PCA (RP-PCA) estimator of Lettau and Pelger (2020a,b) to extract the underlying pricing latent factors entering the SDF in the three-pass estimation.

The three-pass analysis corroborates and adds to the findings documented using the two-pass and spanning analyses. The main takeaways are the following. First, SRP_{HML} is driven almost entirely by the priced sources of currency risk. This is because SRP_{HML} is strongly related to the key latent factors that enter the currency SDF. Second, 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. Third, the inclusion of the SRP portfolios in the cross-section of test assets is not central to the recovery of the SRP_{HML} risk premium, which is symptomatic of a rather strong factor, being priced in many currency investment strategies (see, Giglio, Xiu, and Zhang, 2022). At the same time, by excluding the SRP portfolios from the cross-section, the maximal Sharpe ratio of the tangency portfolios spanned by the latent factors decreases; thus, by investing also in the SRP portfolios, one moves closer to the currency mean-variance efficient frontier. Finally, we find that the three-pass estimate of the SRP_{NT} risk premium is economically large and statistically significant, and the Sharpe ratio of the de-noised return-based SRP_{NT} is also high. Overall, SRP_{NT} qualitatively behaves very much like its tradable counterpart, SRP_{HML} .

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 results from implementing conventional asset pricing tests, and Section 6 presents the key findings from applying the three-pass method. Finally, 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; Menkhoff et al., 2012a; Lettau, Maggiori, and Weber, 2014; Kojen et al., 2018), currency momentum (e.g., Menkhoff et al., 2012b, Asness, Moskowitz, and Pedersen, 2013), 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).

Until recently, however, common practice has been mainly 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).⁴ 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 but more detailed option data, Jurek (2014) quantifies its impact in the order of one third.⁵ The relevance of crash/skewness risk in explaining carry returns also emerges

⁴It is common to hear that the currency carry trade is tantamount to picking up pennies in front of a steamroller (e.g., Pedersen, 2015).

⁵An 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

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 they can help pricing the spread in carry returns (and in other strategies).⁶ 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 and evaluating its pricing performance across a broad set of currency investment strategies rather than only carry portfolios.

A recent paper by Chernov, Dahlquist, and Lochstoer (2023) examines the currency pricing factors for G10 exchange rates, and find that an SDF including carry, value and momentum can explain a large fraction of priced risk. 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 large cross-section of currency portfolios, Nucera, Sarno, and Zinna (2023) 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 (premiums) 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

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 from semivariances, using the information in both 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.

⁶Londono and Zhou (2017) show that the U.S. equity variance risk premium helps predict currency returns.

theirs.

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 sharply 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, consistent with the notion that what ultimately matters for pricing currency portfolio returns is the asymmetry of the distribution (skewness).⁷ 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 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).⁸ 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.⁹ 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 rationalize why rare but extreme disasters can be an important determinant of currency risk premia and rationalize a positive average excess return from carry trades.

⁷Bollerslev, 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.

⁸This 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.

⁹Kelly 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.

3. (Semi)Variance and Skewness Risk Premium

In this section, we detail the construction of currency variance, semivariances, and skewness risk-premium signals, which are our main 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, 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. 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, construction of moment risk premia requires $\mathbb{P}$ and $\mathbb{Q}$ estimates, which we describe next.

3.1. Objective ($\mathbb{P}$) Measures

To start with, we measure variance for currency i at the end of month t ($\sigma_{i,t}^2$) with the realized variance, defined as the summation of squared daily log returns of the spot exchange rate — expressed as units of domestic currency per unit of foreign currency i — in the previous τ months,

$$\sigma_{i,t}^2 \approx RV_{i,t} = \frac{12}{\tau} \sum_{l=0}^{21 \times \tau} r_{i,t-l}^2. \quad (1)$$

Then, following Barndorff-Nielsen, Kinnebrock, and Shephard (2010), we approximate upside and downside semivariances of currency i ($\sigma_{i,u,t}^2$ and $\sigma_{i,d,t}^2$, respectively) as follows,

$$\sigma_{u,i,t}^2 \approx RV_{i,t}^+ = \frac{12}{\tau} \sum_{l=0}^{21 \times \tau} r_{i,t-l}^2 \mathbb{1}_{r_{i,t-l} > 0}, \quad (2)$$

$$\sigma_{d,i,t}^2 \approx RV_{i,t}^- = \frac{12}{\tau} \sum_{l=1}^{21 \times \tau} r_{i,t-l}^2 \mathbb{1}_{r_{i,t-l} \leq 0}, \quad (3)$$

where $\mathbb{1}_{r_{i,t-l}>0}$ ($\mathbb{1}_{r_{i,t-l}\leq 0}$) is an indicator function that takes the value of 1 if the $t-l$ return is positive (negative), and zero otherwise. It holds that $RV_{i,t} = RV_{i,t}^+ + RV_{i,t}^-$.

By taking the difference between upside and downside semivariances, one easily obtains a measure of asymmetry,

$$\sigma_{u,i,t}^2 - \sigma_{d,i,t}^2 \approx RVUD_{i,t} = RV_{i,t}^+ - RV_{i,t}^-, \quad (4)$$

which has been employed successfully by a number of recent studies in equities (see, e.g., Patton and Sheppard, 2015; Feunou, Jahan-Parvar, and Okou, 2018; Bollerslev, Li, and Zhao, 2020).¹⁰

We further normalize the above asymmetry measure in Eq. (4) by the (total) variance, and obtain a relative asymmetry measure as follows,

$$\frac{\sigma_{u,i,t}^2 - \sigma_{d,i,t}^2}{\sigma_{i,t}^2} \approx RSK_{i,t} = \frac{RV_{i,t}^+ - RV_{i,t}^-}{RV_{i,t}}. \quad (5)$$

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 (RVUD) 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 measure in equities). Hence, this normalization is particularly useful when conducting a cross-sectional analysis.

More importantly, the normalized measure satisfies the properties that a skewness

¹⁰This measure of asymmetry in Eq. (4) 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. 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 testing the robustness of the estimates by using mean-adjusted returns in the construction of upside and downside measures of semivariance. Moreover, Bollerslev, Li, Patton, and Quaadvlieg (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. We will return to this issue in the empirical section.

measure should have, such that (under mild conditions) its expectation equals conditional skewness (see, e.g., Feunou, Jahan-Parvar, and Tedongap, 2016).¹¹ For this reason, we refer to this measure of normalized asymmetry as realized skewness.¹² Estimation of skewness is notoriously difficult as computation of the third central moment is very sensitive to outliers and data frequency (e.g., Bollerslev, Li, Patton, and Quaadvlieg, 2020; Bollerslev, 2021). A nice feature of our measure of realized skewness is that it is easy to construct and is robust as it only depends on the second moment (e.g., Feunou, Jahan-Parvar, and Tedongap, 2016), and connects with the relative signed jump measure, which has been shown to be a powerful variable to predict asset returns (e.g., Bollerslev, Li, and Zhao, 2020).

Finally, to construct the objective expectations of total variance, semivariances and realized skewness, which ultimately enter the computation of the associated moment risk premia, we recur to recursive estimations of autoregressive forecasting models (e.g., Bollerslev, Tauchen, and Zhou, 2009).¹³ In what follows, we denote objective (or realized) expected variance with $\widetilde{RV}_{i,t} \equiv \mathbb{E}^{\mathbb{P}}[RV_{i,t+1}|\mathcal{F}_t]$; upside and downside variances

¹¹ Assume that the return, r , is a unimodally distributed random variable with mode m . Then, 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.

¹² Bollerslev, Li, and Zhao (2020) refer to this normalized measure as the relative signed jump variation. Feunou, Jahan-Parvar, and Okou (2018) use the terms (relative) signed jump and realized skewness interchangeably. As explained before, in our empirical analysis, we use daily data to construct the realized measures, so that the interpretation of relative signed jump is not exact. For this reason, we refer to the measure of Eq. (5) simply as (realized) skewness, although we know that it coincides with the relative signed jump when using high-frequency data.

¹³ Given that variance and semivariances are very persistent processes, following the literature, we recur to ARX(1) models to obtain one-month ahead forecasts. Using notation local to this footnote, we recursively estimate $RV_{i,t+1} = \alpha_i + \beta_i RV_{i,t} + \gamma_i IV_{i,t} + \epsilon_{i,t}$, 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, $RV_{i,t+1|t}^+$ and $RV_{i,t+1|t}^-$, and $RVUD_{i,t+1|t}$ is predicted as the difference between the forecasted upside and downside semivariances. To forecast next-month realized skewness, $RSK_{i,t+1|t}$, we recursively estimate simple AR(1) models, as we find that there is no gain in using risk-neutral skewness ($ISK_{i,t}$; defined in Eq. (11)), as additional predictor. As before, we use random walk models to obtain forecasts for the first year.

with $\widetilde{RV}_{i,t}^+ \equiv \mathbb{E}^{\mathbb{P}}[RV_{i,t+1}^+|\mathcal{F}_t]$ and $\widetilde{RV}_{i,t}^- \equiv \mathbb{E}^{\mathbb{P}}[RV_{i,t+1}^-|\mathcal{F}_t]$, respectively; asymmetry with $\widetilde{RVUD}_{i,t} \equiv \mathbb{E}^{\mathbb{P}}[RVUD_{i,t+1}|\mathcal{F}_t]$; and skewness with $\widetilde{RSK}_{i,t} \equiv \mathbb{E}^{\mathbb{P}}[RSK_{i,t+1}|\mathcal{F}_t]$.

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

Next, we follow the model-free methods proposed by Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003) to infer the associated 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.

Consider the time- t price of a variance contract on currency i that pays off the squared log return on the spot exchange rate at time $t + \tau$,

$$IV_{i,t} \equiv e^{-(i_t - i_{i,t})\tau} \mathbb{E}^{\mathbb{Q}}[r_{i,t+\tau}^2|\mathcal{F}_t], \quad (6)$$

where i_t and $i_{i,t}$ are, respectively, the domestic risk-free interest rate and the foreign interest rate of currency i , τ is the time to maturity in years, and $\mathbb{E}^{\mathbb{Q}}$ defines the expectation under the risk-neutral measure $\mathbb{Q}$. Bakshi, Kapadia, and Madan (2003) show that $IV_{i,t}$ can be extracted from the out-of-the-money call and put option prices as follows

$$IV_{i,t} = \int_{S_{i,t}}^{\infty} \frac{2\left(1 - \log\left(\frac{K_i}{S_{i,t}}\right)\right)}{K_i^2} C(t, \tau; K_i) dK_i + \int_0^{S_{i,t}} \frac{2\left(1 + \log\left(\frac{S_{i,t}}{K_i}\right)\right)}{K_i^2} P(t, \tau; K_i) dK_i, \quad (7)$$

where $S_{i,t}$ is the spot exchange rate, $C(t, \tau; K_i)$ and $P(t, \tau; K_i)$ represent call and put prices, and K_i is the corresponding strike price. $IV_{i,t}$ is then the forward-looking expected risk-neutral variance over the next τ period conditioning on information at time t .¹⁴

Furthermore, we define an upside semivariance contract that pays off the squared positive log return, and a downside semivariance contract that pays off the squared negative

¹⁴A point that is often bypassed in using Eq. (7) is that in theory it can admit negative variances. However, this would only arise under extreme values of OTM options. This is also one of the reason 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).

log return. Their time- t prices are given by

$$IV_{i,t}^+ \equiv e^{-(i_t - i_{i,t})\tau} \mathbb{E}^{\mathbb{Q}} \left[r_{i,t+\tau}^2 \mathbb{1}_{r_{i,t+\tau} > 0} | \mathcal{F}_t \right], \quad IV_{i,t}^- \equiv e^{-(i_t - i_{i,t})\tau} \mathbb{E}^{\mathbb{Q}} \left[r_{i,t+\tau}^2 \mathbb{1}_{r_{i,t+\tau} \leq 0} | \mathcal{F}_t \right], \quad (8)$$

where $\mathbb{1}_{r_{i,t+\tau} > 0}$ ($\mathbb{1}_{r_{i,t+\tau} \leq 0}$) is an indicator function that takes the value of 1 if the $t + \tau$ return is positive (negative), and zero otherwise. Using the method of Bakshi, Kapadia, and Madan (2003), it holds that

$$IV_{i,t}^+ = \int_{S_{i,t}}^{\infty} \frac{2 \left(1 - \log \left(\frac{K_i}{S_{i,t}} \right) \right)}{K_i^2} C(t, \tau; K_i) dK_i, \quad (9)$$

$$IV_{i,t}^- = \int_0^{S_{i,t}} \frac{2 \left(1 + \log \left(\frac{S_{i,t}}{K_i} \right) \right)}{K_i^2} P(t, \tau; K_i) dK_i, \quad (10)$$

so that also implied variance equals the sum of upside and downside semivariances (e.g., Andersen, Bondarenko, and Gonzalez-Perez, 2015; Bollerslev, 2021), that is, $IV_{i,t} = IV_{i,t}^+ + IV_{i,t}^-$. For example, 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.

Using $IV_{i,t}^+$, and $IV_{i,t}^-$, one can then easily obtain the forward-looking risk-neutral measure of asymmetry $IVUD_{i,t} = IV_{i,t}^+ - IV_{i,t}^-$ for currency i implied in option prices. Finally, similar to the construction of its objective counterpart in Eq. (5), expected risk-neutral skewness is given by normalizing the asymmetry measure ($IVUD_{i,t}$) by the total variance measure ($IV_{i,t}$), as follows

$$ISK_{i,t} = \frac{IV_{i,t}^+ - IV_{i,t}^-}{IV_{i,t}}. \quad (11)$$

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.

In both cases, by normalizing the numerator by variance, the resulting measures quantify asymmetry both across time and in the cross section.

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 to predict asset returns in different markets. For example, Della Corte, Ramadorai, and Sarno (2016) were among the first to show that individual currency variance risk premia help predict the cross-section of currency returns, resulting in a profitable trading strategy. Formally, the variance risk premium is defined as the difference between the objective and risk-neutral expected quadratic variations (QV), which can be well approximated by the difference in (expected) realized and option-implied variances (see, e.g., Bollerslev, Tauchen, and Zhou, 2009),

$$\begin{aligned} VRP_{i,t} &= \mathbb{E}^{\mathbb{P}}[QV_{i,t+1}|\mathcal{F}_t] - \mathbb{E}^{\mathbb{Q}}[QV_{i,t+1}|\mathcal{F}_t] \\ &= \widetilde{RV}_{i,t} - IV_{i,t}, \end{aligned} \quad (12)$$

where $\widetilde{RV}$ and IV are defined in Sections 3.1 and 3.2, respectively. Moreover, we decompose the variance risk premium into its upside and downside components,

$$VRP_{i,t} = \underbrace{(\widetilde{RV}_{i,t}^+ - IV_{i,t}^+)}_{VRPU_{i,t}} + \underbrace{(\widetilde{RV}_{i,t}^- - IV_{i,t}^-)}_{VRPD_{i,t}} \quad (13)$$

whereby $VRPU_{i,t}$ and $VRPD_{i,t}$ 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 com-

ponents of VRP,¹⁵

$$\begin{aligned}
 VPUD_{i,t} &= \mathbb{E}^{\mathbb{P}}[RV_{i,t+1}^+ - RV_{i,t+1}^- | \mathcal{F}_t] - \mathbb{E}^{\mathbb{Q}}[RV_{i,t+1}^+ - RV_{i,t+1}^- | \mathcal{F}_t] \\
 &= \widetilde{RVUD}_{i,t+1} - IVUD_{i,t+1} \\
 &\approx VRPU_{i,t} - VRPD_{i,t}.
 \end{aligned} \tag{14}$$

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

$$SRP_{i,t} = \widetilde{RSK}_{i,t} - ISK_{i,t}, \tag{15}$$

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), our 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 Later we will show that such measures behave very differently empirically from our skewness measure.

¹⁵Feunou, 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 fulfil entirely the conditions for a skewness measure set in Groeneveld and Meeden (1984). Therefore, we simply refer to it as the asymmetry risk premium.

¹⁶Kozhan, 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 very 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.

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 currencies 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. Note that it is important to employ a relatively large cross-section of individual currencies including both safe and emerging currencies for examining skewness risk, as it 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 volume associated with currencies outside the G10 is very 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

¹⁷From the 2019 BIS Triennial Survey, for example, the average net daily total turnover in US 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 US dollars was about 7bn for Amazon and 6bn for Apple stocks.

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 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 3.2 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 (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

$$X_{i,t+1} = \frac{S_{i,t+1} - F_{i,t}}{S_{i,t}}, \quad (16)$$

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

$$X_{i,t+1} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \frac{S_{i,t} - F_{i,t}}{S_{i,t}} \approx r_{i,t+1} + (i_{i,t} - i_t), \quad (17)$$

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, 2023, 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. The table shows that the annualized currency returns 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 both the implied and realized downside semivariances (IVD and RVD) are larger than their respective upside semivariances (IVU and RVU), suggesting that these measures of risk-neutral and realized skewness are both negative on average. The skewness risk premium (SRP) is positive on average: it has a mean of 0.18 and a standard

deviation of 0.34, which means that 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).¹⁸ The skewness risk premium is left-skewed with a skewness of -0.45, and its kurtosis is slightly larger than 3.

4.2. Currency 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 represent the set of test assets and provide some competing factors in our empirical analysis.

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 5.64% with a t -statistic of 3.35, and its annualized Sharpe ratio is 0.80. The long-short portfolio returns are left-skewed and 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 5.33% ($t = 2.67$) and whose annualized Sharpe ratio is about 0.63; the short portfolio (P1) displays an annualized mean excess return of only about -0.31%, which is not statistically significant, with a tiny annualized Sharpe ratio.

¹⁸Recall that we define the exchange rate as FCU/USD, so that when S_i decreases, foreign currency i depreciates relative to the USD. Thus, a positive SRP_i is consistent with investors pricing an even larger depreciation in the foreign currency under the risk-neutral than under the objective measure.

We decompose 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. (17). The results, presented in Panel B of Table 1, suggest that the spot returns of the quintile portfolios do not have any 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 an increasing, monotonic tendency, with the long-short portfolio showing a positive and highly statistically significant average interest-rate differential. 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 Farhi and Gabaix (2016) rare disaster model, 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 returns 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

¹⁹As discussed in Section 3, we implement two additional robustness exercises. First, we construct the realized measures of semivariances used to construct SRPs by demeaning the spot returns in the selected window, following Bollerslev (2021)'s suggestion. We find that such demeaning has a negligible impact

Before turning to the fully-fledged asset pricing analysis, we 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. Table A3, in the Internet Appendix, shows that SRP_{HML} earns an annualized mean return of only 2.02%, 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 6.15%, which is highly statistically significant ($t = 3.30$). 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 currencies, which are notoriously more prone to sudden stops in capital flows and speculative attacks. However, the Sharpe ratio is higher when trading both developed and emerging currencies than when only trading emerging currencies (0.80 vs 0.76). In addition, we note that despite that the G10 SRP risk premium is not statistically significant over the full sample, it is strongly significant prior to the financial crisis (Figure A1). 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

on the evidence of Table 1; above all, the properties of the SRP_{HML} factor remain essentially the same. Second, we sort currencies into portfolios by replacing our measure of SRPs based on semivariances with standard measures of SRPs 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 by using 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 SRPs 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 measures of SRPs constructed from semivariances are easy to construct and more robust than those relying on the central third moment.

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 when is most needed, i.e., in bad times. Hence, the overall high average return would be compensation for the inherent riskiness of the strategy.²⁰

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} . We plot the SRP nontradable factor in the lower panel 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 0.47.

This way of constructing a nontradable factor from characteristics is not novel, and closely relates 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).²¹

²⁰We perform our empirical analysis using the HML SRP tradable factor, 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 0.65 and 0.64, and their returns have skewness of -0.87 and -0.71, 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.

²¹For example, Kojien 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.

Specifically, the spread in factor characteristics tends to widen when the factor's return premium is expected to be large. The positive and high correlation between SRP_{HML} and SRP_{NT} suggests a similar relationship between expected currency returns and our SRP nontradable factor based on the cross-sectional signal dispersion.

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 (premium) more directly than its tradable counterpart, SRP_{HML} . This is because, by construction, SRP_{HML} combines skewness risk premium (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 premium 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.

Portfolios Sorted on SRP_{NT} Betas. While it is common practice in the literature to sort currencies (or other assets) on characteristics, beta sorts are an alternative common means to analyze risk premium in financial markets (e.g., Ang et al., 2006). If SRP_{NT} is a priced factor, then one should also expect portfolios sorted on currency risk exposures to SRP_{NT} (betas) to generate significant spreads in mean returns. That is, currencies that yield low returns when SRP_{NT} is low (high beta currencies) should earn higher return in equilibrium, whereas currencies that hedge against skewness risk (low beta currencies) should trade at a premium. We therefore sort currencies into five portfolios based on their past individual exposures to SRP_{NT} . Following the literature (e.g., Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a), we measure the risk exposures (or time-varying quantity of risk) using rolling estimates of betas with a window of 36 months.

We report the summary statistics of the beta-sorted currency portfolios in the Internet Appendix (Table A4). The resulting evidence is consistent with a risk-return interpretation. In fact, we find that investing in currencies with high SRP_{NT} betas offers a much

higher return than investing in currencies with low SRP_{NT} betas. The high-minus-low beta portfolio earns an annualized mean return of 4.15% with a t -ratio of 2.43 and an annualized Sharpe ratio of 0.52. Portfolio mean returns monotonically increase with respect to SRP_{NT} betas. Hence, the higher the quantity of skewness risk (as measured by SRP_{NT} rolling betas), the higher the portfolio excess return. Meanwhile, the beta spread portfolio (P5-P1) has a rather high correlation of 0.63 with SRP_{HML} , which suggests that these beta-sorted portfolios, albeit not identical, are very similar to the portfolios sorted on individual currency SRPs.

Overall, this simple beta-sort analysis is consistent with the conjecture that currency risk exposures to SRPs, and hence skewness risk, matter for understanding the cross-section of currency returns. Moreover, it lends support to the use of SRPs as sorting variable to construct a tradable factor that captures currencies' exposures to skewness risk.

Test Assets and Competing Factors. Finally, 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; Kroenke, 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 VPUD signals (see Section 3). 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. To conclude, 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 A5 reports summary statistics of the portfolios associated with the 11 investment strategies. We find that CAR, VAL, and MOMS long-short strategies earn large and statistically significant mean excess returns, while MOMM, VRPD, VRPUD and NFA display marginally statistically significant mean excess returns (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 VAL and MOMS (0.44 and 0.40), 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).²² Nevertheless, in our sample SRP has an even higher Sharpe ratio than any of the 11 strategies considered (see Tables 1 and A5). 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 A5). 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 (2020), and with the notion that skewness in the economy translates to skewness in asset returns.

²²While 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.

Strategies that rely on signals from options also show excess returns that are strongly negatively skewed, with VRPD and VPRU 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 (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 A6, in the Internet Appendix). We find that among the top-3 currencies that feature most often in SRP P1, there are JPY and CHF (85% and 68%), two safe funding currencies, in addition to HKD (74%). 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 display the highest turnover in the constituents of the corner portfolios.

Finally, we turn to inspect the efficient portfolio frontiers (Figure 3, Panel B). To isolate the impact of CAR and SRP, we consider four frontiers that are constructed using: 12 HML factors and the Dollar factor (i.e., all factors); all factors excluding the CAR factor; all factors excluding the SRP factor; and all factors excluding both the CAR and SRP factors. We focus on CAR and SRP not only because they are the two most profitable strategies, but also because they are highly correlated. The resulting evidence is clearcut. The efficient frontier (solid line) moves southeast slightly more when excluding SRP (dashed line) than when excluding CAR (dash-dotted line), and it shifts dramatically southeast when both CAR and SRP factors are excluded (dotted line). This evidence is reflected in Sharpe ratios of the tangency portfolios on those four frontiers: their annualized Sharpe ratios are 1.25, 1.13, 1.12, and 0.87, respectively. The figure also shows that SRP essentially lies on the frontier constructed including the Dollar factor and all the long-short factors except SRP and CAR, suggesting that one can achieve almost the same Sharpe ratio by trading either SRP alone or the other strategies together (excluding CAR); we will examine this point in depth in the factor spanning regressions.

Summing Up. In sum, this analysis shows that 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, and the improvement turns out to be substantial if CAR is excluded from the original frontier. This in turn suggests that SRP is not subsumed by the other currency strategies, and its inclusion helps expand the frontier; however, SRP and CAR appear to be closely linked together, given that by replacing one with the other the efficient frontier is essentially unchanged. At the same time, many strategies have negatively skewed returns, while MOMS has positive skewed returns, so that MOMS is likely to be disconnected or only weakly associated with SRP. Next, we turn to analyze these issues more formally through asset pricing tests.

5. Asset Pricing Tests

In this section, we perform cross-sectional asset pricing tests using the conventional two-pass Fama-MacBeth (FMB) and GMM estimators (see the Internet Appendix, Section IV, for a detailed description of the estimators). We first focus on the SRP portfolios and then assess larger cross-sections covering up to a cross-section of 55 currency portfolios associated with the 11 investment strategies. To start with, 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

$$m_t = 1 - b_{DOL}(DOL_t - \mu_{DOL}) - b_{SRP}(SRP_t - \mu_{SRP}). \quad (18)$$

When turning to larger cross-sections, we also assess SDFs of expanding dimensions, whereby we add other relevant control factors (e.g., CAR, MOMS, VAL). We also resort to factor spanning regressions to shed further light on the *true* currency risk factors, without relying on specific cross-sections of test assets.

5.1. Pricing SRP Portfolios ($N = 5$)

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).

We perform this cross-sectional analysis in Table 2, using both FMB two-pass regressions and the GMM estimation of the SDF. In Panel A, the SDF features the DOL and SRP tradable factors, i.e. $SRP_t = SRP_{HML}$ in Eq. (18). The test assets consist of the five SRP portfolios. Following Lewellen, Nagel, and Shanken (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), and in doing so we gain one extra degree of freedom in statistical tests. Consistently, we find that the two-pass risk-premium estimate of SRP_{HML} is 5.67%, being very close to its sample mean (5.64%) and highly statistically significant, with a t -statistic above 3 (Panel A.I). The cross-sectional adjusted R^2 is 83%, and the p -value of the χ^2 test is 0.13, so that we cannot reject the null that the pricing errors – the *alphas* 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 Eq. (18), 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 of 3.29, 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 Eq. (18). According to the two-pass method, the estimate of the annualized risk premium of SRP_{NT} is about 2.07% and is highly statistically significant (Panel B.I).²³ The cross-sectional adjusted R^2 drops to 65% (relative to 83% in Panel A.I), which is not surprising in light of the

²³The model-implied estimate of the SRP_{HML} premium is about 5.30% (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 5.78%, which is very close to its sample average.

nontradable nature of the factor, and the χ^2 test suggests that we reject the null that the pricing errors are jointly equal to zero. Nevertheless, the GMM estimate of $b_{SRP_{NT}}$ is about 0.11 and is very precisely estimated, with a t -statistic above 3. In line with the FMB evidence, the χ^2 test rejects the null that the alphas are jointly zero.

This evidence clearly shows that (i) the SRP factors, either tradable or nontradable, are priced in SRP portfolios, and that (ii) the SDF using the tradable SRP factor prices entirely the cross-section of SRP portfolios, while this is not the case for the SDF using the nontradable SRP factor. In light of its superior pricing performance, 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.

5.2. Pricing Currency Portfolios ($N = 55$)

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 more 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, Xiu, and Zhang, 2022). 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, we implement cross-sectional asset pricing tests using the same two-factor SDFs as in the previous section, but using various larger cross-sections of test assets, by grouping strategies that display similar properties/signals. We present the asset pricing analysis for the two-factor tradable SDF, including the DOL and SRP_{HML} factors, in Table 3.

In Panel A, we take as test assets the portfolios from CAR, NFA, and RR ($N = 15$).²⁴ The FMB analysis shows that the SRP_{HML} risk-premium estimate is about 5.16%, which is very close to its sample average (Panel A.I). The cross-sectional adjusted R^2 is about 0.79, and the χ^2 test has a p -value of 0.15, suggesting that the pricing errors are statistically jointly equal to zero. Turning to the GMM estimates (Panel A.II), b_{SRP} is

²⁴As before, we include the SRP HML factor as an additional test asset in each of the cross-sections considered.

about 0.01 with a t -statistic of 2.79, the risk-premium estimate of SRP_{HML} is precisely estimated, and the χ^2 test does not reject the null of zero pricing errors (p -value of about 0.16).

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 5.51%, which is again highly statistically significant and not different from its sample average (Panel B.I). The cross-sectional adjusted R^2 is about 0.52 and yet the χ^2 test suggests that all alphas are statistically insignificantly different from zero (p -value = 0.15). According to the GMM estimates, the SDF parameter b_{SRP} is about 0.01 with a t -statistic above 3, and the χ^2 test fails to reject the null of zero pricing errors (Panel B.II).

In Panel C, we study the four option-based risk-premium strategies, namely VRP, VRPD, VRPU, and VRPUD ($N = 20$). 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 $N = 55$ 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 rather 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 4.53%, which remains statistically significant at the 1% level and close to the factor sample average. The cross-sectional adjusted R^2 is 0.62 and the χ^2 test has a p -value of 0.10 using FMB (Panel D.I) and of 0.09 using GMM (Panel D.II). Thus, we cannot reject the null of zero pricing errors at the 5% level but we marginally reject it at the 10% level, which seems understandable as we use a two-factor SDF to price a broad cross-section of assets. Moreover, the estimate of b_{SRP} is fairly stable (around 0.008) and is statistically significant with a t -statistic of 2.35.

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). Each panel

refers to a different cross-section. The main takeaway is that, regardless of the cross section, the average test asset returns lie around the 45-degree line, suggesting a rather accurate pricing performance. Not surprisingly the cross-section including MOM and VAL strategies shows the lowest fit (Panel B).

We then examine how the two-factor model performs when we replace the SRP_{HML} factor with the nontradable factor, SRP_{NT} . Table A7 in the Internet Appendix implements the same empirical tests as those of Table 3 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%. As before, we find that based on these two-factor models, the model with the tradable SRP_{HML} factor performs better than that with the nontradable SRP_{NT} factor in terms of standard goodness of fit measures.

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/value (Panel B) and full (Panel D) cross sections, it is clear that the model fits less well for momentum and value 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, first by pricing the cross-section of 55 test assets with larger pricing models (Section 5.3), and then by recurring to simple factor spanning regressions that do not hinge upon the test assets and yet help detect in a simple way the *true* tradable factors entering the SDF (Section 5.4).

5.3. Pricing Currency Portfolios ($N = 55$) with Larger SDFs

At first, using standard methods and relatively small cross-sections, the literature has shown that currency carry (e.g., Lustig et al., 2011), currency momentum (e.g., As-

ness et al., 2013; Menkhoff et al., 2012b), and currency value (e.g., Asness et al., 2013; Menkhoff et al., 2017) generate significant average excess returns which are not highly correlated with each other. In a recent study, using recently developed methods and a large cross section of test assets, Nucera, Sarno, and Zinna (2023) show that at least three and potentially four latent factors should enter the currency SDF. Three of these factors appear to be closely related, albeit not identical, to the carry, short-term momentum, and value tradable factors (the other factor is essentially a leveraged Dollar factor). Therefore, CAR, MOMS, and VAL are natural control factors to add to the SDF.

To start with, we consider the MOMS factor, which as the prior analysis suggests, has more distinct properties from our SRP factor (e.g., MOMS is positively skewed), and hence is more likely to be omitted from the SDF. Thus, in Table IV, Panel A presents the results from using the SRP HML factor, together with DOL and MOMS. The test assets consist of the 55 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 4.99%, which is highly statistically significant and not different from the factor's sample average. The risk-premium estimate of the MOMS factor is about 3.19%, which is also statistically significant and not different from the MOMS sample average. The cross-sectional adjusted R^2 is about 0.72, which is roughly 10% higher than that based on the previous two-factor model (Panel D, Table 3). Furthermore, the GMM estimate of b_{SRP} is about 0.009 with a t -statistics of 2.73, and the estimate of b_{MOMS} is about 0.005 with a t -statistic of 2.09. 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 0.16 and 0.12, respectively). 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_{HML} .

Having established that MOMS should also enter the SDF, in Table A8 of the Internet Appendix, we carry out further analysis, by moving to four-factor models which include either the CAR (Panel A.I) or VAL (Panel B.I) factors.²⁵ We find that neither of these factors contain extra pricing information beyond SRP_{HML} and MOMS. Moreover, we

²⁵Given 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° , to mitigate multicollinearity problems. Later on, we will provide additional analysis on the close relation between SRP and CAR.

show that, when SRP_{HML} is left out from the SDF, the b_{CAR} estimate obtained by GMM is statistically significant and hence CAR enters the SDF (Panel C). We find very similar results by replacing the tradable SRP factor with its nontradable counterpart (see Panel B of Table IV and Panels A.II and B.II of Table A8).

Summing up, the two-pass analysis suggests that the pricing kernel should include both the SRP and MOMS factors. If the SRP factor is replaced with the CAR factor, the evidence is similar. These multiple pieces of evidence arise in a standard asset pricing two-pass setting, whereby the model is evaluated with respect to the cross-sections of test assets employed. To limit concerns on the selection of the test assets, we have relied on a large cross-section (as well as on several smaller cross-sections). Next, to corroborate some of these findings, we recur to simple factor spanning regressions that, among other things, help us discern the *true* pricing factors from the subsumed ones without relying on specific choices of the test assets (e.g., Barillas and Shanken, 2017).

5.4. Factor Spanning Regressions

To begin with, we assess whether any of the competing factors can explain the excess returns of the SRP HML factor. Specifically, in Panel A of Table 5, we run the following spanning regressions

$$SRP_t = \alpha_j + \beta_j f_{j,t} + \epsilon_{j,t}, \quad j = 1, \dots, J, \quad t = 1, \dots, T, \quad (19)$$

where the dependent variable is the SRP_{HML} tradable factor, and the regressor $f_{j,t}$ is the selected j -th competing HML factor (i.e., CAR, NFA, ..., etc.). The resulting evidence is clearcut: none of the factors except CAR is able to explain the excess returns of SRP_{HML} . In fact, except for the first regression on CAR, all the *alphas* are highly statistically significant (with t -statistics above 3). In the spanning regression on CAR, the *alpha* is not statistically significant, albeit not negligible in economic terms (1.68% annualized), the *beta* is about 0.67 and is highly statistically significant, and the R^2 is about 61% (the highest across all regressions).²⁶ Therefore, these estimates show that

²⁶In the Internet Appendix (Panel C, Table A9), we also add the DOL factor as control and find that the results are essentially unchanged.

the SRP factor displays a close link with CAR, confirming our earlier evidence, and is not subsumed by any of the other factors.

We then reverse the exercise and assess whether the SRP HML factor can explain returns of the competing HML factors by performing the following spanning regressions

$$f_{j,t} = \alpha_j + \beta_j SRP_t + \epsilon_{j,t}, \quad j = 1, \dots, J, \quad t = 1, \dots, T. \quad (20)$$

Using this setup, the goal is to compare the factor model $F_j = [f_j, SRP]$ with the nested model $F_0 = [SRP]$ (Barillas and Shanken, 2017; Barillas et al., 2020). A positive and statistically significant *alpha* implies that the maximal Sharpe ratio improves significantly, i.e. $SR(F_j) > SR(F_0)$. Similarly, the GRS test (Gibbons, Ross, and Shanken, 1989) is equivalent to testing whether the maximal Sharpe ratio resulting from all the 12 factors is significantly larger than the Sharpe ratio one can achieve by investing only in the SRP HML factor.

Panel B shows that all the *alpha* estimates are much lower than the respective factor average returns. Notably, only the *alpha* of the MOMS regression is both positive and marginally statistically significant (Panel D of Table A9 in the Internet Appendix shows that the result is robust to adding DOL as a control).²⁷ This clearly lends support to our previous two-pass analysis showing that MOMS should also enter the currency SDF along with the SRP factor. Moreover, we find that the SRP HML factor fully explains excess returns of the CAR factor. In comparison with the earlier CAR spanning regression (Panel A), the *alpha* now is even smaller and the *beta* higher. The GRS test does not reject the null that all *alphas* are jointly equal to zero at the significance level of 5%. All together, those tests suggest that combining any of the competing factors (notably except MOMS) with the SRP factor cannot improve the Sharpe ratio significantly, consistent with our previous analyses.

Finally, given that SRP and CAR have similar Sharpe ratios and appear to mutually explain each other, we replace SRP with CAR in Eq. (20). Thus, we assess if CAR is able to jointly explain the other 11 HML factors (10 competing factors plus the SRP HML factor). Panel E of Table A9 in the Internet Appendix shows that this is not the

²⁷The *alphas* from the regressions of the factors of VRPD and VPUD are also marginally significant but negative, on the backdrop of weakly statistically significant average returns.

case. In fact, we find that 5 out of 11 *alpha* estimates are statistically significant, at least at the 10% significance level. Moreover, the GRS test rejects the null with a p -value of 0.02. Thus, unlike SRP, CAR cannot jointly explain the excess returns of the other 11 HML factors.

Taken together the above evidence confirms that both the MOMS and SRP factors should enter the SDF, and that SRP and CAR are closely related factors but with a somewhat different pricing performance. On the one hand, the SRP factor prices all the other strategies except MOMS, thus indicating that MOMS should feature in the SDF. On the other hand, the analysis clearly shows that SRP is not subsumed by other factors except by CAR. Indeed, SRP and CAR mutually explain each other. However, the analysis also indicates that between the two, SRP performs better than CAR in pricing the other strategies. Thus, in our sample, one should prefer SRP over CAR in the SDF. Overall, the results from the spanning regressions confirm but also strengthen our earlier evidence.

6. Three-Pass Analysis

Thus far, we have documented a set of important results by sorting individual currencies on their skewness risk premia and performing conventional asset pricing tests. The two main results are as follows. First, we discover a new currency strategy with a high Sharpe ratio that exploits the predictive power of currency skewness risk premia for currency excess returns. Second, based on the two-pass procedure, we establish that the SRP HML factor (SRP_{HML}) helps price many currency portfolio returns. In fact, we find that by including SRP_{HML} in the SDF, most commonly used currency factors are no longer pricing factors. These findings are largely confirmed using simple factor spanning regressions.

In this section, we shed further light on these findings by means of the augmented three-pass estimator recently employed by Nucera, Sarno, and Zinna (2023) to model a large cross-section of currency portfolios and to obtain robust risk premia estimates of a long list of potential currency risk factors. The estimator combines the three-pass estimator developed by Giglio and Xiu (2021), GX hereafter, and the risk-premium PCA

(RP-PCA) estimator of Lettau and Pelger (2020a,b), LP hereafter. Importantly, the three-pass estimator of GX helps address the omitted-factor and measurement-error problems inherent in the two-pass estimation of factor risk premia. To do so, it projects the candidate risk factors onto the latent factors spanning the ‘optimal’ SDF implied in the cross-section of test assets.

However, the three-pass estimator 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. 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 PCA estimator). By doing so, it 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 better span all relevant sources of priced risk. Meanwhile, one can recur to several economic diagnostic criteria to inspect the properties of the SDF recovered via RP-PCA. We briefly review the RP-PCA three-pass estimator in Section V.1 in the Internet Appendix.

Overall, by using the RP-PCA three-pass estimator, we can gauge further insights on the properties of the SRP tradable factor, SRP_{HML} , complementing our prior analysis. Above all, we aim at providing further evidence about its strength and information content, for example, by drawing a connection with the priced (and unpriced) sources of currency risk. In doing so, we also provide robust estimates of the risk premium of SRP_{HML} , which we contrast with those of the HML factors associated with the other investment strategies. Therefore, the use of the three-pass estimator is useful to shed further light on the properties of the SRP tradable factor, and its connection with the other investment strategies. At the same time, its use is key to achieve a robust risk premium estimate of the nontradable SRP factor, SRP_{NT} .

In short, we will show that the SRP tradable and nontradable risk factors appear to be tightly linked together with the priced sources of currency risk. We present the main findings next, while we provide the fully-fledged three-pass analysis in Section V.2 of the

Internet Appendix.

Main Findings. To start with, we extract the latent factors via RP-PCA from the panel of 60 portfolios constructed based on the signals from the 12 investment strategies (thus, including the 5 SRP portfolios). We then recover the currency latent-factor SDF, shedding light on its properties (Table 6). Taken together, the analysis shows that a five-factor SDF provides a very accurate pricing performance, but even slightly more parsimonious models can deliver small pricing errors for most strategies.

The interpretation of the first four factors is clearcut (Table 7). While F_1 is close to a level “Dollar factor” (individual portfolios have similar positive risk exposures), the remaining factors are clearly slope factors. Specifically, F_2 is a “Carry” factor, F_3 is a “Momentum” factor, and F_4 is “long Value short (long-term) Momentum” factor. This evidence is in line with the one provided by Nucera, Sarno, and Zinna (2023), despite the two studies focus on substantially different samples. However, the inclusion of option strategies helps us refine the factors’ interpretation.

Moreover, the three-pass analysis shows that SRP_{HML} is driven almost entirely by the priced sources of currency risk. This is because SRP_{HML} is strongly related to the latent factors that undoubtedly enter the currency SDF. Indeed, we can accurately recover the SRP_{HML} risk premium using even parsimonious latent-factor models (Table 8), consistent with the notion that skewness or crash risk (premiums) are priced sources of currency risk. Moreover, the three-pass 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. By contrast, the carry factor is almost entirely explained by the second latent factor that is essentially irrelevant for momentum strategies (e.g., see Figure 5), in line with the evidence uncovered by Nucera, Sarno, and Zinna (2023).

The analysis also shows that the inclusion of the SRP portfolios in the cross-section of test assets is not central to the recovery of the SRP_{HML} risk premium, which is symptomatic of a rather strong factor, being priced in many currency investment strategies (see, Giglio, Xiu, and Zhang, 2022). 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. In fact, an accurate recovery of their risk 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 portfolios spanned by the latent factors decreases; thus, by investing also in the SRP portfolios, one moves closer to the currency mean-variance efficient frontier.

Consistent with the factor spanning regression results, we further show that by combining any individual currency strategy with SRP_{HML} in the sense of Asness, Moskowitz, and Pedersen (2013), one achieves a higher Sharpe ratio than the one of the original strategy. It is also interesting that the Sharpe ratios from combining the three-pass “de-noised” factors are in many cases even higher than the Sharpe ratios from combining the corresponding observable factors. The two extreme cases are of particular interest. At one hand of the spectrum, by combining SRP_{HML} with carry, the Sharpe ratio improvement is negligible, which is a manifestation of the close nexus between the two strategies; put simply, skewness risk seems to be a key source of risk for carry. At the other end of the spectrum, the gain is large when combining SRP_{HML} with the short-term momentum (or value) factor, in light of their weak correlation and different skewness properties, resulting in large diversification benefits.

Finally, we assess how the SRP nontradable factor behaves in the three-pass estimation. 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 (Giglio and Xiu, 2021) highly desirable. We find that the three-pass estimate of the SRP_{NT} risk premium is economically large and statistically significant, and the Sharpe ratio of the de-noised return-based SRP_{NT} is also high. Moreover, the estimate of its risk premium is somewhat lower than that of SRP_{HML} but remains accurate even when the SRP portfolios are dropped from the cross-section of test assets. Overall, SRP_{NT} qualitatively behaves very much like its tradable counterpart, SRP_{HML} .²⁸

²⁸By 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

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 broad cross-sections of portfolio excess returns, employing both conventional and recent asset pricing methods (which control for omitted variables and measurement errors), and also using a nontradable SRP factor, SRP_{NT} .

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. In particular, our findings are broadly consistent with the theoretical predictions of the currency rare disaster model of Farhi and Gabaix (2016).

Overall, 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 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 variance 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 rather than aversion to variance risk as such.

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 accounts for omitted-variable and measurement-error biases.

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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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	-0.31 (-0.26)	1.14 (0.67)	0.99 (0.56)	0.10 (0.05)	5.33 (2.67)	5.64 (3.35)
STD	5.59	7.98	8.59	8.66	8.45	7.03
SR	0.06	0.14	0.12	0.01	0.63	0.80
Skew	0.39	-0.19	-0.29	-0.57	-0.65	-0.64
Kurt	4.50	3.82	4.82	4.47	4.78	4.88
AC	0.02	0.05	0.03	0.10	0.15	0.18
Panel B: SRP Portfolio Components						
	P1	P2	P3	P4	P5	HML
r	0.72 (0.60)	1.28 (0.77)	0.21 (0.12)	-2.42 (-1.24)	-1.37 (-0.72)	-2.09 (-1.35)
fd	-1.03 (-7.38)	-0.14 (-1.01)	0.79 (4.87)	2.52 (12.2)	6.70 (15.4)	7.74 (16.1)
Panel C: $\mathbb{P}$ and $\mathbb{Q}$ Skewness Portfolios						
	P1	P2	P3	P4	P5	HML
$\mathbb{P}$ Leg	1.95 (1.11)	2.25 (1.21)	0.56 (0.33)	1.67 (0.99)	0.81 (0.55)	-1.15 (-0.88)
$\mathbb{Q}$ Leg	3.22 (1.58)	1.99 (0.99)	1.95 (1.11)	-0.07 (-0.04)	-0.21 (-0.17)	-3.43 (-1.86)

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^2 s (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	1.329	5.668	7.05	λ	1.271	2.071	10.5
(NW)	(0.90)	(3.32)	[0.13]	(NW)	(0.86)	(2.84)	[0.03]
(Sh)	(0.92)	(3.39)		(Sh)	(0.88)	(3.43)	
	RMSE	Adj. R^2			RMSE	Adj. R^2	
	0.88	0.83			1.29	0.65	
A.II GMM				B.II GMM			
	DOL	SRP_{HML}	χ^2		DOL	SRP_{NT}	χ^2
b	-0.002	0.010	7.08	b	-0.001	0.108	11.8
	(-0.64)	(3.29)	[0.13]		(-0.20)	(3.14)	[0.02]
λ	1.329	5.668		λ	1.271	2.071	
	(0.95)	(3.94)			(0.88)	(3.18)	

Table 3: 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 ($N = 20$) cross-sections, and for the entire cross-section consisting of the $N = 55$ 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 20 portfolios from the VRP, VRPU, VRPD, and VPUD strategies; (D) the 55 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^2 s (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	1.502	5.155	19.3	λ	1.436	5.506	25.5
(NW)	(1.05)	(3.06)	[0.15]	(NW)	(0.99)	(3.24)	[0.15]
(Sh)	(1.05)	(3.34)		(Sh)	(1.00)	(3.66)	
	RMSE	Adj R^2			RMSE	Adj R^2	
	0.77	0.79			0.93	0.52	
A.II GMM				B.II GMM			
GMM	DOL	SRP_{HML}	χ^2	GMM	DOL	SRP_{HML}	χ^2
b	-0.001	0.009	19.1	b	-0.002	0.010	26.9
	(-0.38)	(2.79)	[0.16]		(-0.52)	(3.12)	[0.11]
λ	1.502	5.155		λ	1.436	5.506	
	(1.07)	(3.37)			(1.02)	(3.69)	
C. VRP, VRPD, VRPU, VRPUD				D. All 55 Portfolios			
C.I FMB				D.I FMB			
FMB	DOL	SRP_{HML}	χ^2	FMB	DOL	SRP_{HML}	χ^2
λ	1.521	4.415	14.5	λ	1.484	4.529	67.4
(NW)	(1.06)	(2.59)	[0.75]	(NW)	(1.03)	(2.66)	[0.10]
(Sh)	(1.06)	(2.81)		(Sh)	(1.03)	(2.80)	
	RMSE	Adj R^2			RMSE	Adj R^2	
	0.69	0.76			0.81	0.62	
C.II GMM				D.II GMM			
GMM	DOL	SRP_{HML}	χ^2	GMM	DOL	SRP_{HML}	χ^2
b	-0.000	0.008	14.4	b	-0.001	0.008	68.5
	(-0.16)	(2.35)	[0.76]		(-0.22)	(2.35)	[0.09]
λ	1.521	4.415		λ	1.484	4.529	
	(1.08)	(2.85)			(1.05)	(2.83)	

Table 4: 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 $N = 55$ portfolios associated with the 11 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^2 s (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	1.495	4.994	3.188	64.2	λ	1.482	1.618	3.279	69.1
(NW)	(1.04)	(3.00)	(2.00)	[0.16]	(NW)	(1.03)	(2.77)	(2.05)	[0.08]
(Sh)	(1.04)	(3.13)	(1.98)		(Sh)	(1.03)	(2.89)	(2.03)	
		RMSE	Adj R ²				RMSE	Adj R ²	
		0.69	0.72				0.68	0.73	
A.II GMM					B.II GMM				
	DOL	SRP _{HML}	MOMS	χ ²		DOL	SRP _{NT}	MOMS	χ ²
b	-0.000	0.009	0.005	66.6	b	0.001	0.085	0.006	66.0
	(-0.07)	(2.73)	(2.09)	[0.12]		(0.41)	(2.89)	(2.32)	[0.13]
λ	1.495	4.994	3.188		λ	1.482	1.632	3.581	
	(1.06)	(3.17)	(2.00)			(1.03)	(2.88)	(2.05)	

Table 5: Spanning Regressions

The table presents the results from implementing the spanning regressions using the SRP_{HML} factor (SRP) and the competing factors (f_i), i.e., the HML factors associated with the 11 currency investment strategies. The first two columns present the mean excess returns (Avg.; annualized in percent) and annualized Sharpe ratios (SR) of the competing factors (f). Panel A reports the results from regressing the SRP HML factor on each of the competing factors as in Eq. (19), and Panel B presents the results from regressing each of the competing factors on the SRP HML factor as in Eq. (20). In the bottom rows of Panel B, we present the GRS-test statistic and the corresponding p -value in square brackets. In the last column, we report the spanning regression R^2 s. The Newey-West t -statistics are presented in brackets. The sample period is from February 1998 to December 2021, at monthly frequency.

f_i			A. SRP on f_i (Eq. (19))		B. f_i on SRP (Eq. (20))		R^2
	Avg.	SR	α	β	α	β	
CAR	5.89 (3.27)	0.72	1.68 (1.54)	0.67 (14.9)	0.79 (0.70)	0.90 (19.8)	0.61
NFA	2.80 (1.68)	0.37	4.23 (3.23)	0.50 (7.45)	-0.51 (-0.37)	0.59 (8.60)	0.29
RR	2.62 (1.36)	0.31	4.17 (3.48)	0.56 (9.59)	-2.11 (-1.55)	0.84 (13.8)	0.47
VRP	0.98 (0.65)	0.13	5.13 (3.84)	0.53 (8.96)	-2.22 (-1.63)	0.57 (8.44)	0.30
VRPU	2.69 (1.71)	0.36	3.92 (3.33)	0.64 (10.6)	-1.36 (-1.15)	0.72 (13.5)	0.46
VRPD	2.83 (1.70)	0.35	3.78 (3.52)	0.66 (15.1)	-2.12 (-1.68)	0.88 (14.7)	0.58
VPUD	3.01 (1.67)	0.36	3.68 (3.62)	0.65 (15.2)	-2.27 (-1.95)	0.94 (17.3)	0.61
MOMS	3.04 (1.99)	0.40	5.76 (4.08)	-0.04 (-0.40)	3.29 (1.83)	-0.04 (-0.40)	0.00
MOMM	2.84 (1.75)	0.34	5.28 (3.45)	0.13 (1.71)	1.81 (1.06)	0.18 (1.72)	0.02
MOML	1.73 (0.94)	0.20	5.42 (3.53)	0.13 (2.04)	0.66 (0.37)	0.19 (1.91)	0.02
VAL	3.52 (2.11)	0.44	4.77 (3.09)	0.25 (2.78)	1.71 (0.89)	0.32 (2.87)	0.08
GRS					1.78		
p -value					[0.06]		

Table 6: 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, $k = 1, 2, \dots, 9$. 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, $\bar{\sigma}_\epsilon^2 = \frac{1}{N} \sum_{n=1}^N [Var(\hat{\epsilon}_n)/Var(X_n)]$; 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 $n = 1, \dots, N$ test assets, and $t = 1, \dots, T$ months. *II.b: 2P* presents the second-pass diagnostics: the mean absolute errors (MAE) of the cross-sectional regression, $\bar{X}_n = \hat{\psi}_n \gamma^\top + a_n$, for $n = 1, \dots, N$, 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 $1 \times k$ vector with entries $\hat{b}_{MV,k} = \mu_{F,k} / \sigma_{F,k}^2$, with $\mu_{F,k}$ and $\sigma_{F,k}^2$ 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	
	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\bar{\sigma}_\epsilon^2$	$\overline{RMS}_\alpha$	MAE	$R^2(\%)$	SR	ΔSR
F_1	12.77	0.23	0.04	$\varphi(F_1)$	20.90	1.17	0.87	62.59	0.23	
F_2	7.79***	0.61	0.40	$\varphi(F_{1-2})$	16.16	0.95	0.44	82.83	0.66	0.42
F_3	5.62***	0.62	0.57	$\varphi(F_{1-3})$	13.79	0.86	0.29	92.68	0.90	0.25
F_4	5.77***	0.97	1.37	$\varphi(F_{1-4})$	12.73	0.71	0.14	98.47	1.33	0.42
F_5	3.33**	0.50	0.64	$\varphi(F_{1-5})$	11.57	0.63	0.11	98.86	1.42	0.09
F_6	2.26*	0.40	0.58	$\varphi(F_{1-6})$	10.70	0.59	0.10	99.11	1.48	0.05
F_7	3.01***	0.59	0.97	$\varphi(F_{1-7})$	10.01	0.51	0.07	99.49	1.59	0.11
F_8	0.13	0.03	0.05	$\varphi(F_{1-8})$	9.40	0.50	0.07	99.49	1.59	0.00
F_9	1.92*	0.42	0.76	$\varphi(F_{1-9})$	8.84	0.46	0.07	99.62	1.64	0.05

Table 7: 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, $k = 1, \dots, 6$. Thus, we report the exposures to the first six extracted, orthogonalized latent factors (i.e., $K = 6$). 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						A.II: Explained Variation					
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$
SRP	0.05***	0.41***	0.16***	0.05	-0.08	-0.03	17.84	72.33	76.51	76.61	77.16	77.13
CAR	0.06***	0.53***	0.00	0.09*	-0.19***	-0.04	14.10	82.50	82.44	82.77	85.24	85.29
RR	0.07***	0.49***	-0.25***	-0.06	-0.11***	-0.20***	21.79	75.02	82.13	82.27	82.96	84.63
NFA	0.10***	0.17***	0.02	0.24***	-0.29***	-0.25***	57.00	65.27	65.19	68.58	74.87	78.32
MOMS	-0.02	-0.06	0.45***	0.51***	0.25***	0.13*	1.68	2.54	31.81	47.76	52.56	53.33
MOMM	-0.02	0.10	0.76***	-0.36***	0.12	-0.11**	1.17	2.92	69.43	75.92	76.66	77.18
MOML	-0.03*	0.10**	0.75***	-0.52***	0.09**	0.12**	2.29	4.34	67.71	81.04	81.46	82.05
VAL	0.03***	0.26***	-0.37***	0.57***	-0.01	0.43***	5.36	22.94	40.93	58.74	58.60	68.27
VRP	0.05***	0.34***	-0.11**	-0.41***	-0.23***	0.50***	13.26	48.92	50.64	61.80	66.21	82.15
VRPD	0.08***	0.47***	-0.05*	-0.16**	-0.27***	0.23***	26.93	80.36	80.58	81.94	86.75	89.39
VRPU	0.06***	0.35***	0.07	0.19***	0.02	-0.54***	19.14	55.24	55.87	57.98	57.88	75.31
VRPUD	0.08***	0.50***	0.00	-0.05	-0.22***	-0.05	26.57	83.45	83.39	83.44	86.32	86.38

Table 8: 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 $k = 2, \dots, 6$. 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			$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$			$\varphi(F_{1-6})$		
	μ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR
SRP	5.64***	(1.65)	0.80	3.88***	(1.31)	0.65	4.78***	(1.39)	0.78	5.07***	(1.40)	0.82	4.79***	(1.41)	0.77	4.73***	(1.43)	0.76
CAR	5.88***	(1.79)	0.72	4.85***	(1.61)	0.66	4.85***	(1.63)	0.66	5.34***	(1.67)	0.72	4.70***	(1.67)	0.62	4.59***	(1.68)	0.61
RR	2.62	(1.89)	0.31	4.78***	(1.63)	0.64	3.36*	(1.72)	0.43	2.99*	(1.72)	0.38	2.61	(1.71)	0.33	2.17	(1.76)	0.27
NFA	2.80*	(1.61)	0.37	2.68**	(1.34)	0.44	2.78**	(1.35)	0.45	4.16***	(1.33)	0.66	3.20**	(1.37)	0.49	2.64*	(1.43)	0.39
MOMS	3.04*	(1.56)	0.40	-0.75*	(0.39)	-0.56	1.77*	(1.04)	0.41	4.70***	(1.20)	0.90	5.53***	(1.28)	1.01	5.82***	(1.31)	1.05
MOMM	2.84*	(1.63)	0.34	0.51	(0.68)	0.32	4.77***	(1.56)	0.68	2.68	(1.69)	0.36	3.06*	(1.68)	0.41	2.80	(1.70)	0.38
MOML	1.73	(1.82)	0.20	0.49	(0.64)	0.25	4.70***	(1.55)	0.67	1.67	(1.73)	0.22	1.97	(1.73)	0.26	2.24	(1.72)	0.29
VAL	3.52***	(1.67)	0.44	2.50**	(0.95)	0.65	0.40	(1.14)	0.08	3.67***	(1.31)	0.60	3.65**	(1.41)	0.59	4.63***	(1.47)	0.70
VRP	0.98	(1.50)	0.13	3.29***	(1.05)	0.65	2.67**	(1.09)	0.51	0.30	(1.28)	0.05	-0.47	(1.28)	-0.08	0.67	(1.34)	0.10
VRPD	2.83*	(1.70)	0.35	4.62***	(1.54)	0.64	4.35***	(1.55)	0.60	3.41**	(1.62)	0.46	2.52	(1.64)	0.33	3.04*	(1.64)	0.40
VRPU	2.69*	(1.55)	0.36	3.50***	(1.27)	0.63	3.91***	(1.26)	0.70	4.99***	(1.26)	0.88	5.07***	(1.26)	0.89	3.85***	(1.42)	0.60
VRPUD	3.01*	(1.80)	0.36	4.91***	(1.68)	0.64	4.94***	(1.68)	0.64	4.68**	(1.77)	0.61	3.95**	(1.80)	0.50	3.84**	(1.78)	0.49

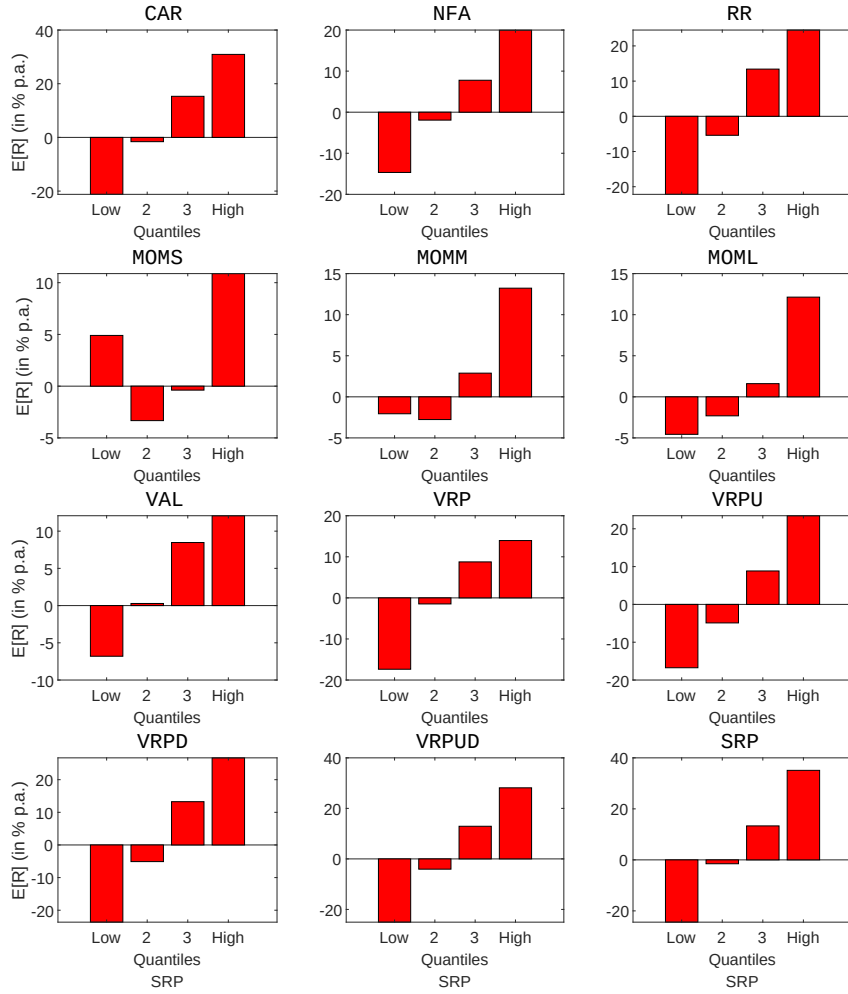


Figure 1: Currency Investment Strategies and the SRP HML Factor

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 ($T = 287$).

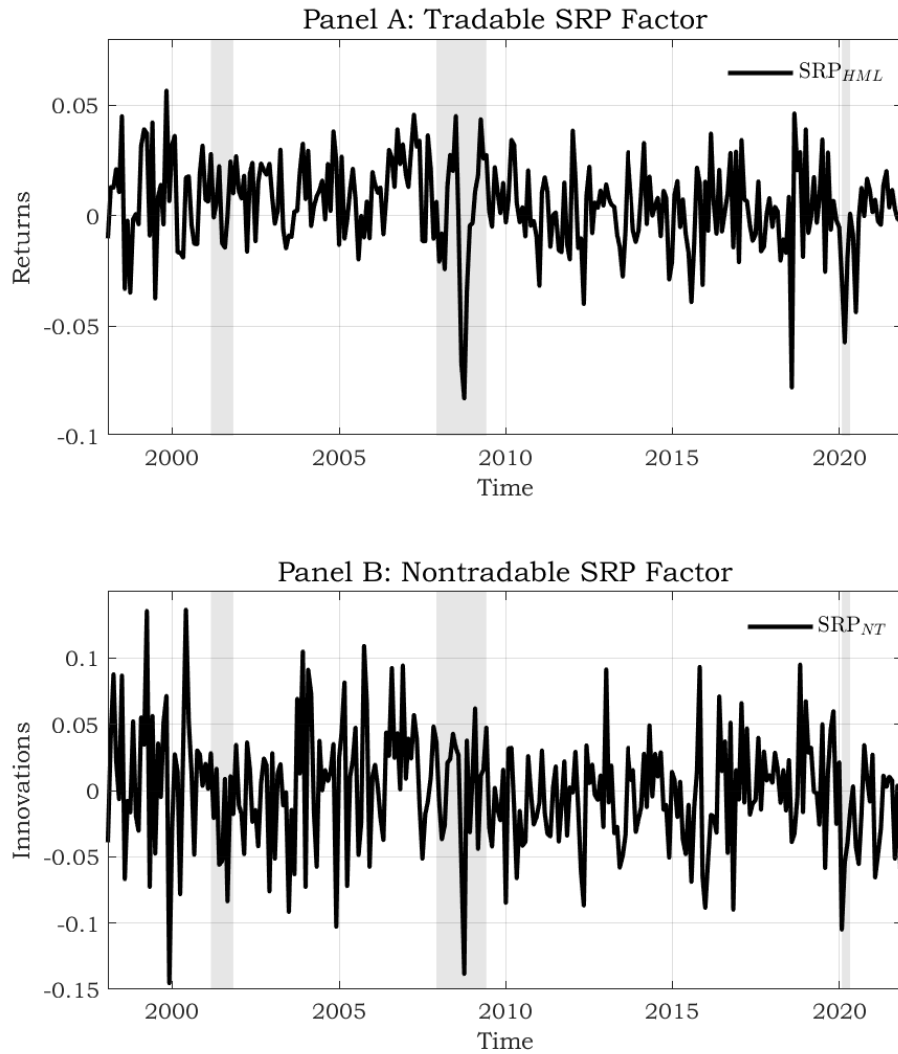


Figure 2: Tradable and Nontradable SRP Factors

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 ($T = 287$).

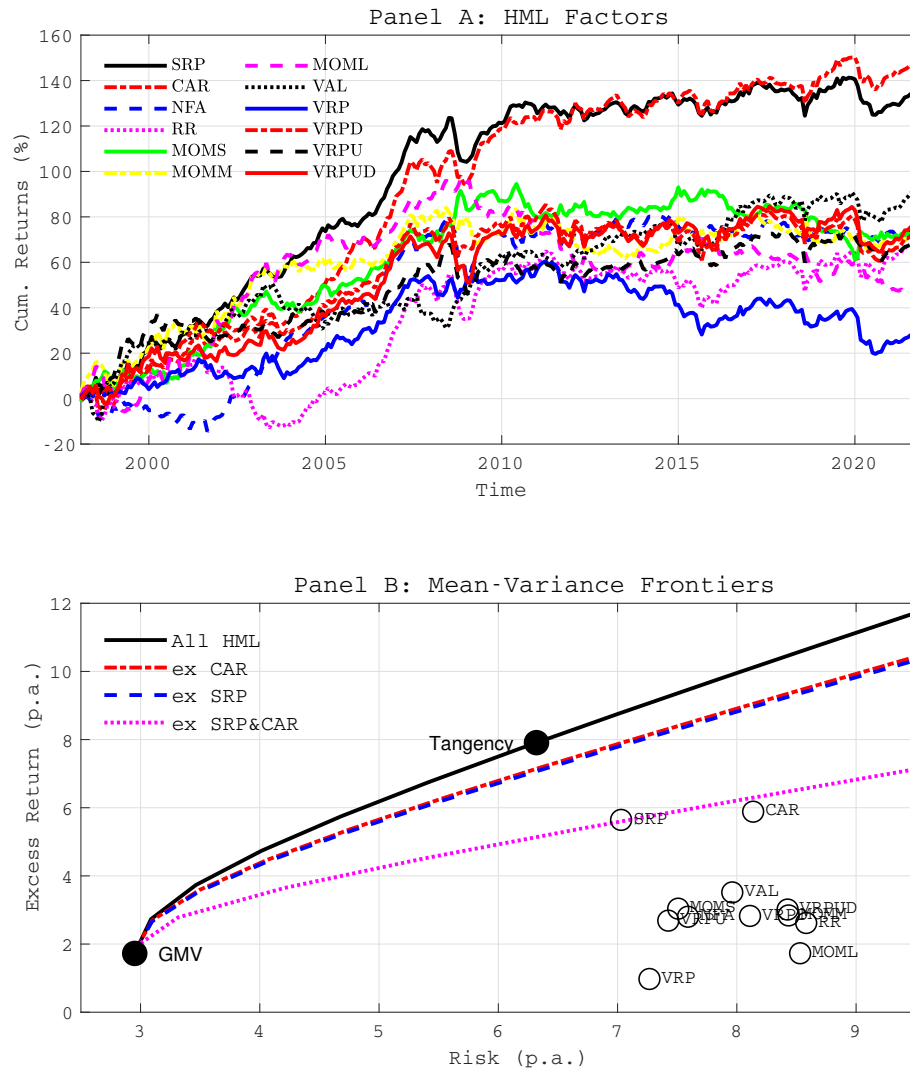


Figure 3: Factor Returns and Mean-Variance Frontiers

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 four 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; (ii) all factors except the CAR factor; (iii) all factors except the SRP factor; (iv) all factors except the SRP and CAR factors. 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 ($T = 287$).

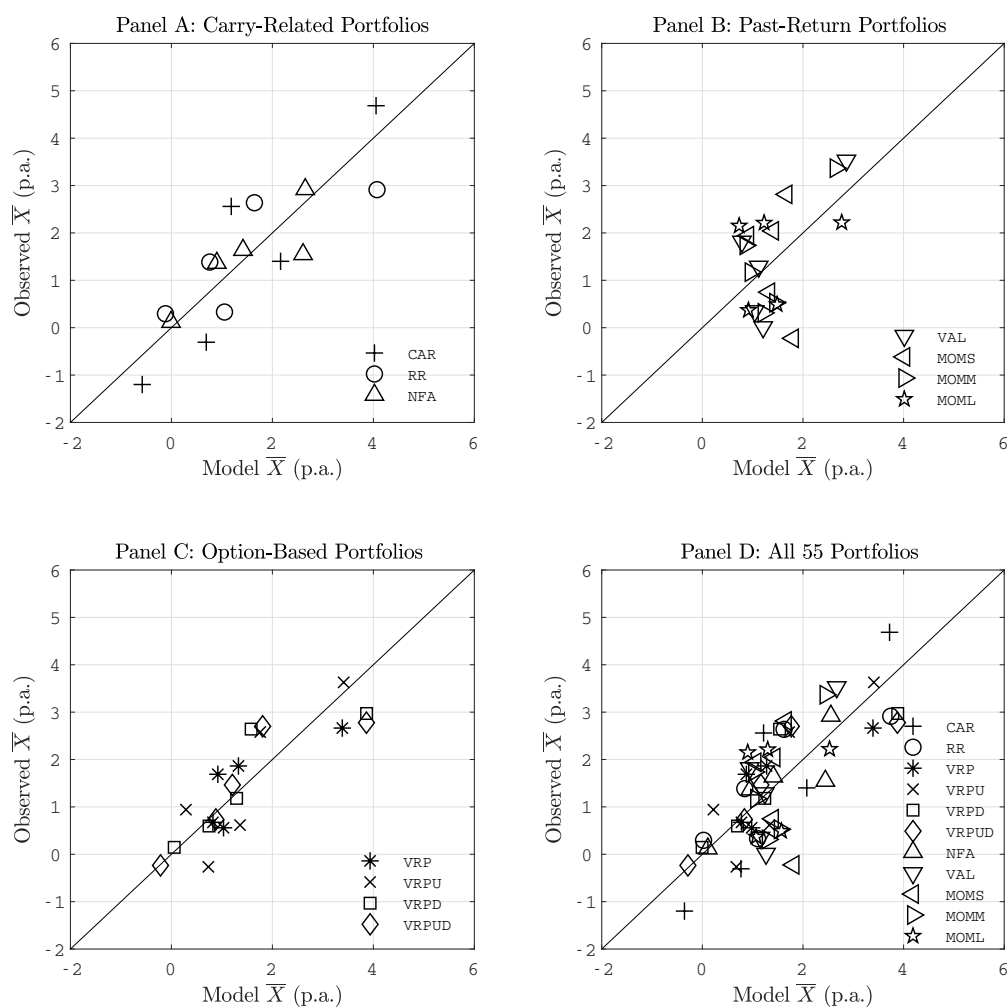


Figure 4: Observed vs. Model-Implied Expected Returns

The figure shows the observed, realized mean excess returns versus the the two-pass model-implied mean excess returns obtained from the two-factor SDF, including the Dollar factor and the SRP HML factor (i.e., estimates from Table 2). Each panel refers to a different cross-section, including the portfolios from the indicated strategies. Excess returns are in percent, annualized (p.a.). The sample period is from February 1998 to December 2021 at monthly frequency ($T = 287$).

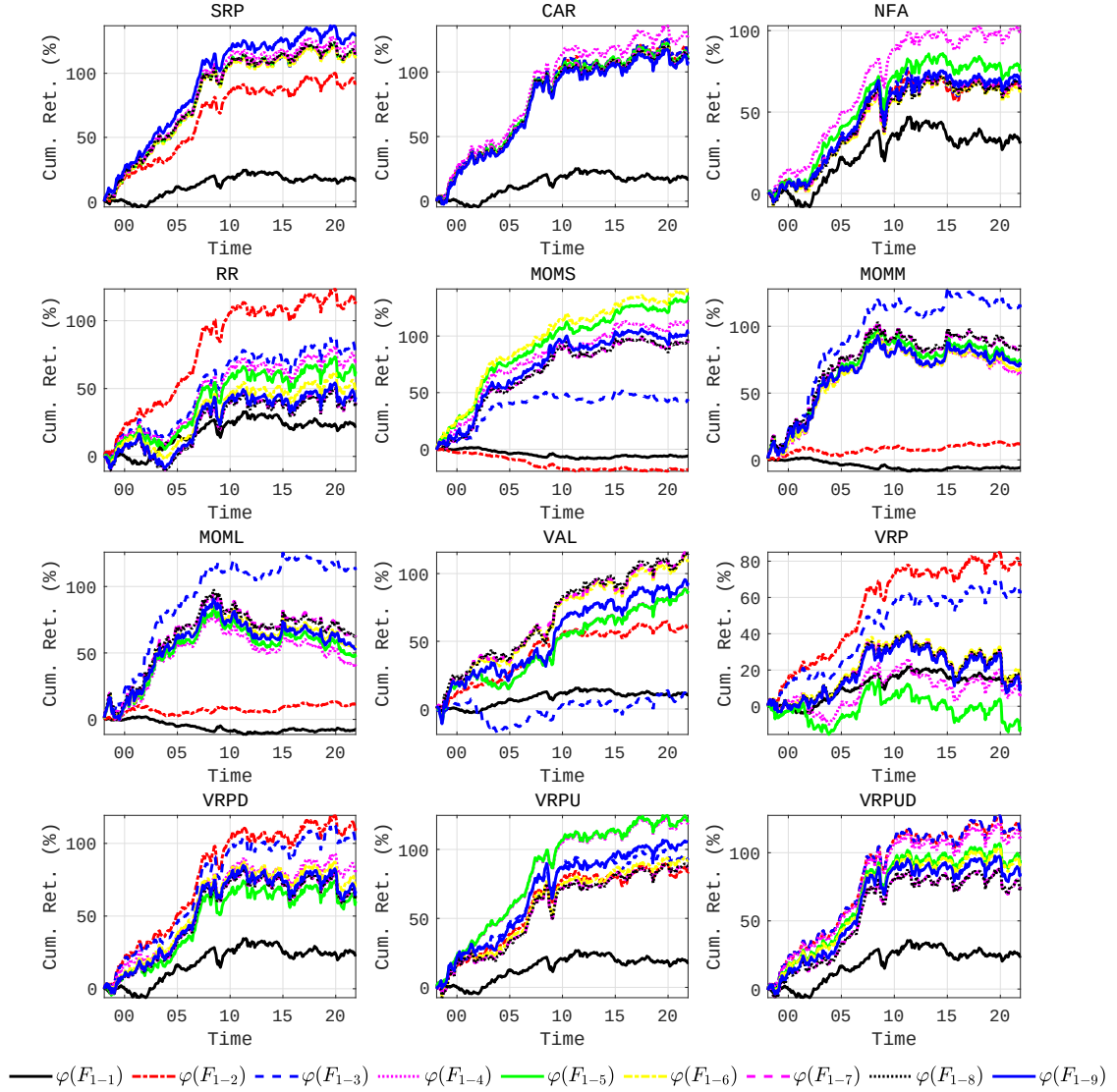


Figure 5: De-noised HML Factors by SDF Dimension

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 nine de-noised versions by expanding the dimension of the factor model, i.e., $\varphi(F_{1-k})$ with $k = 1, 2, \dots, 9$. 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 ($T = 287$).

Internet Appendix
(not for publication)

Skewness Risk Premia and the Cross-Section of
Currency Returns

by

Junye Li, Lucio Sarno and Gabriele Zinna

Table of Contents:

- **Section I:** Risk-Neutral Variance and Semivariances
- **Section II:** Data and Summary Statistics
- **Section III:** Currency Investment Strategies
- **Section IV:** Two-Pass Inference
- **Section V:** Three-pass Inference and Analysis

I. Risk-Neutral Variance and Semivariances

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

$$IV_{i,t}^+ = \int_{S_{i,t}}^{\infty} \frac{2 \left(1 - \log\left(\frac{K_i}{S_{i,t}}\right) \right)}{K_i^2} C(t, \tau; K_i) dK_i, \quad (\text{I.1})$$

$$IV_{i,t}^- = \int_0^{S_{i,t}} \frac{2 \left(1 + \log\left(\frac{S_{i,t}}{K_i}\right) \right)}{K_i^2} P(t, \tau; K_i) dK_i. \quad (\text{I.2})$$

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 Kohlhaugen (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 Kohlhaugen (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. (2023), 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 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 US 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 (ATM) delta-neutral straddles, 10 delta and 25 delta risk-reversals, and 10 delta and 25 delta butterfly spreads. The sample period is from January 1998 to December 2021.

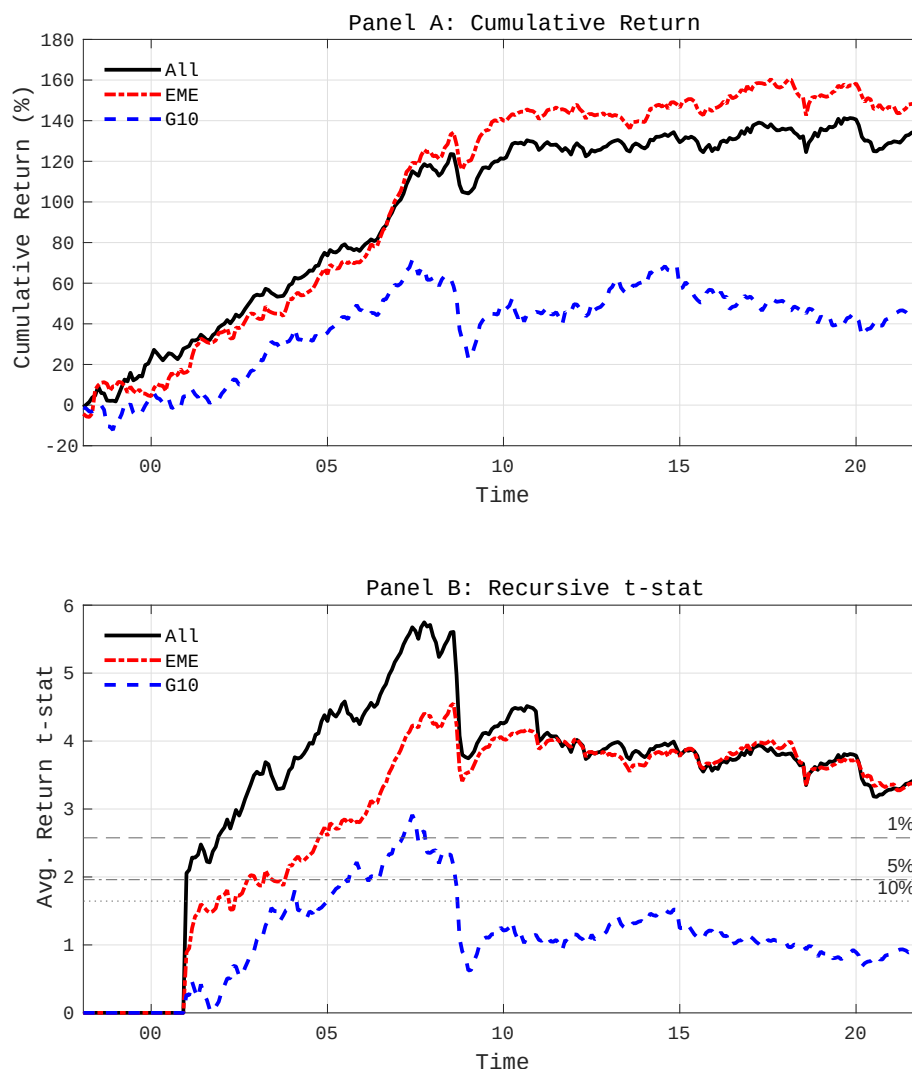
			Realized Measures			Implied Measures		
	CRet	SRP	RV	RVU	RVD	IV	IVU	IVD
Mean	0.013	0.175	0.011	0.005	0.006	0.015	0.005	0.010
STD	0.105	0.340	0.017	0.008	0.010	0.021	0.005	0.017
Skew	-0.374	-0.447	8.080	7.107	8.824	8.763	4.518	9.711
Kurt	7.222	3.791	110.1	89.98	124.0	141.8	42.38	168.6
Q05	-0.549	-0.397	0.000	0.000	0.000	0.001	0.001	0.001
Q50	0.008	0.191	0.007	0.003	0.003	0.010	0.004	0.006
Q95	0.594	0.704	0.033	0.015	0.017	0.042	0.012	0.031

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	-0.73 (-0.42)	1.62 (0.86)	1.62 (0.74)	0.15 (0.08)	1.29 (0.56)	2.02 (0.93)
STD	7.96	8.89	9.54	9.30	10.47	9.49
SR	0.09	0.18	0.17	0.02	0.12	0.21
Skew	0.36	0.10	0.07	-0.21	-0.33	-1.09
Kurt	3.87	3.86	3.57	4.56	4.70	6.95
Panel B: 18 Emerging Currencies						
	P1	P2	P3	P4	P5	HML
Mean	0.06 (0.05)	0.93 (0.60)	0.08 (0.04)	3.19 (1.49)	6.21 (2.96)	6.15 (3.30)
STD	5.41	7.77	8.98	9.84	9.13	8.10
SR	0.01	0.12	0.01	0.32	0.68	0.76
Skew	-1.33	-0.11	-0.49	-0.16	-0.65	0.06
Kurt	14.98	4.32	4.64	4.90	5.59	6.15

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.

Table A4: Portfolios Sorted on SRP_{NT} Betas

The table presents the performance of the portfolios constructed by sorting currencies on their estimated past risk exposures to SRP_{NT} . For each currency, we estimate the time-varying betas by performing rolling time-series regressions of the currency excess returns on SRP_{NT} using 36-month rolling windows, following Lustig et al. (2011) and Menkhoff et al. (2012a), among others. We then allocate 20% of currencies with the lowest betas to Portfolio 1 (P1) and 20% of currencies with the highest betas to Portfolio 5 (P5). As we move from P1 to P5, the portfolios include currencies with increasing betas. 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. The Newey-West t -statistics are presented in brackets. The sample period is from January 1999 to December 2021, at a monthly frequency.

	P1	P2	P3	P4	P5	HML
Mean	-0.31 (-0.21)	0.81 (0.50)	1.28 (0.81)	1.37 (0.77)	3.84 (1.77)	4.15 (2.43)
STD	6.90	7.23	7.22	8.25	9.73	7.99
SR	0.04	0.11	0.18	0.17	0.40	0.52
Skew	0.16	-0.37	-0.27	-0.19	-0.77	-0.45
Kurt	3.11	4.48	4.48	4.25	5.55	3.78

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 A5).

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 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 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., 2023), 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.

Variance Risk-Premium Strategies (VRP, VRPU, VRPD, and VPUD). 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 (VPUD) – upside minus downside VRP – strategy we allocate to P1 currencies with low VPUDs and to P5 currencies with high VPUDs. 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 A5: 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 (-0.86) [0.19]	-0.31 (-0.21) [-0.10]	2.56 (1.51) [-0.14]	1.40 (0.73) [-0.44]	4.69 (2.23) [-0.69]	5.88 (3.27) [-0.47]	0.72
NFA	0.12 (0.11) [0.16]	1.37 (0.81) [-0.14]	1.64 (1.01) [0.22]	1.55 (0.89) [-0.66]	2.92 (1.27) [-0.66]	2.80 (1.68) [-0.93]	0.37
RR	0.29 (0.22) [0.62]	1.39 (0.81) [0.08]	0.33 (0.20) [-0.20]	2.64 (1.58) [-0.39]	2.91 (1.32) [-0.61]	2.62 (1.36) [-0.51]	0.31
VRP	1.69 (1.11) [-0.14]	0.67 (0.49) [0.02]	0.56 (0.32) [-0.33]	1.86 (1.13) [0.07]	2.66 (1.27) [-0.86]	0.98 (0.65) [-0.65]	0.13
VRPU	0.94 (0.59) [-0.03]	-0.27 (-0.17) [-0.16]	0.62 (0.42) [-0.37]	2.58 (1.41) [-0.05]	3.63 (1.66) [-0.58]	2.69 (1.71) [-0.37]	0.36
VRPD	0.15 (0.11) [0.28]	0.60 (0.43) [0.12]	1.18 (0.68) [0.00]	2.64 (1.52) [-0.31]	2.97 (1.34) [-0.81]	2.83 (1.70) [-0.77]	0.35
VPUD	-0.24 (-0.17) [0.28]	0.74 (0.52) [0.00]	1.46 (0.92) [0.07]	2.70 (1.47) [-0.42]	2.78 (1.23) [-0.80]	3.01 (1.67) [-0.63]	0.36
MOMS	-0.22 (-0.12) [-0.63]	0.75 (0.43) [-0.56]	1.94 (1.11) [-0.13]	2.04 (1.28) [0.15]	2.81 (1.70) [-0.02]	3.04 (1.99) [0.52]	0.40
MOMM	0.53 (0.27) [0.00]	1.74 (1.02) [-0.36]	1.17 (0.82) [0.14]	0.31 (0.19) [-0.34]	3.37 (1.81) [-0.63]	2.84 (1.75) [0.01]	0.34
MOML	0.49 (0.24) [0.08]	2.15 (1.38) [0.00]	0.37 (0.22) [-0.05]	2.21 (1.35) [-0.45]	2.22 (1.24) [-0.67]	1.73 (0.94) [-0.10]	0.20
VAL	0.01 (0.01) [-0.48]	1.82 (1.21) [-0.09]	0.35 (0.22) [-0.20]	1.29 (0.74) [-0.34]	3.53 (1.75) [-0.03]	3.52 (2.11) [-0.07]	0.44

Table A6: 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	0.37	INR	0.47	DKK	0.35	INR	0.52
TWD	0.46	RUB	0.48	CZK	0.37	IDR	0.53
CHF	0.68	MXN	0.52	TWD	0.59	MXN	0.61
HKD	0.74	TRY	0.59	JPY	0.85	TRY	0.64
JPY	0.85	IDR	0.62	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	AUD	0.33	BRL	0.45
TWD	0.47	BRL	0.52	NZD	0.35	IDR	0.50
CHF	0.72	TRY	0.53	SGD	0.34	TRY	0.58
HKD	0.73	MXN	0.74	CAD	0.40	ZAR	0.70
JPY	0.86	ZAR	0.82	HKD	0.75	MXN	0.71
E. VRPU				F. VRPD			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
EUR	0.37	BRL	0.44	TWD	0.30	IDR	0.49
SEK	0.42	NZD	0.48	SGD	0.35	BRL	0.53
DKK	0.44	TRY	0.52	HKD	0.66	TRY	0.60
CHF	0.56	HUF	0.53	CHF	0.67	MXN	0.71
JPY	0.69	ZAR	0.70	JPY	0.80	ZAR	0.80
G. VPUD				H. NFA			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
SGD	0.38	HUF	0.50	NOK	0.69	TRY	0.55
HKD	0.41	BRL	0.54	TWD	0.85	PLN	0.69
TWD	0.41	TRY	0.61	SGD	0.90	HUF	0.85
CHF	0.82	MXN	0.67	CHF	1	AUD	1
JPY	0.86	ZAR	0.84	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

IV. 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}

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

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

$$E[m_{t+1}X_{nt+1}] = 0 \Rightarrow E[X_{nt+1}] = \beta'_n \lambda, \quad (\text{IV.2})$$

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

$$X_{nt} = a_n + \beta'_n f_t + \epsilon_{nt}. \quad (\text{IV.3})$$

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,

$$E_T[X_{nt}] = \beta'_n \lambda + \alpha_n, \quad (\text{IV.4})$$

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 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,

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

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 $(b', \mu'_f, \text{vec}(\Sigma_f)')'$. 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.²⁹

²⁹Cochrane (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.”

Table A7: 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 ($N = 20$) strategy cross-sections, and for the entire cross-section consisting of the $N = 55$ 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 20 portfolios from the VRP, VRPU, VRPD, and VPUD strategies; (D) the 55 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^2 s (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				B. MOMS, MOMM, MOML, VAL			
A.I FMB				B.I FMB			
FMB	DOL	SRP_{NT}	χ^2	FMB	DOL	SRP_{NT}	χ^2
λ	1.483	1.715	19.7	λ	1.432	1.986	20.4
(NW)	(1.03)	(2.67)	[0.14]	(NW)	(0.99)	(2.92)	[0.37]
(Sh)	(1.03)	(2.997)		(Sh)	(1.00)	(3.39)	
	RMSE	Adj R^2			RMSE	Adj R^2	
	0.83	0.75			0.93	0.52	
A.II GMM				B.II GMM			
GMM	DOL	SRP_{NT}	χ^2	GMM	DOL	SRP_{NT}	χ^2
b	0.000	0.089	19.7	b	-0.000	0.104	20.2
	(0.08)	(2.80)	[0.14]		(-0.07)	(3.17)	[0.39]
λ	1.483	1.715		λ	1.432	1.986	
	(1.03)	(2.85)			(1.00)	(3.17)	
C. VRP, VRPD, VRPU, VRPUD				D. All 55 Portfolios			
C.I FMB				D.I FMB			
FMB	DOL	SRP_{NT}	χ^2	FMB	DOL	SRP_{NT}	χ^2
λ	1.517	1.407	18.9	λ	1.475	1.423	70.3
(NW)	(1.06)	(2.25)	[0.46]	(NW)	(1.02)	(2.37)	[0.07]
(Sh)	(1.06)	(2.50)		(Sh)	(1.03)	(2.55)	
	RMSE	Adj R^2			RMSE	Adj R^2	
	0.78	0.69			0.84	0.59	
C.II GMM				D.II GMM			
GMM	DOL	SRP_{NT}	χ^2	GMM	DOL	SRP_{NT}	χ^2
b	0.001	0.073	22.0	b	0.001	0.074	68.7
	(0.25)	(2.33)	[0.29]		(0.21)	(2.39)	[0.09]
λ	1.517	1.407	IA - 14 ^{λ}	λ	1.475	1.423	
	(1.06)	(2.39)			(1.03)	(2.45)	

Table A8: 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 55 portfolios from the 11 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^2 s (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	1.490	4.575	3.325	0.264	λ	1.480	1.551	3.347	0.628
(NW)	(1.03)	(2.67)	(2.13)	(0.17)	(NW)	(1.03)	(2.68)	(2.15)	(0.37)
(Sh)	(1.04)	(2.92)	(2.12)	(0.17)	(Sh)	(1.03)	(2.83)	(2.13)	(0.39)
	RMSE	Adj R^2	χ^2			RMSE	Adj R^2	χ^2	
	0.68	0.72	62.5 [0.18]			0.68	0.72	65.3 [0.12]	
GMM	DOL	SRP_{HML}	MOM	CAR^o	GMM	DOL	SRP_{NT}	MOM	CAR^o
b	0.000	0.008	0.006	0.003	b	0.001	0.081	0.006	0.002
	(0.03)	(2.63)	(2.30)	(0.57)		(0.44)	(2.81)	(2.37)	(0.28)
λ	1.490	4.575	3.325	0.264	λ	1.480	1.551	3.347	0.627
	(1.06)	(2.94)	(2.14)	(0.17)		(1.04)	(2.88)	(2.14)	(0.38)
		χ^2					χ^2		
		66.5[0.10]					67.9[0.10]		
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	1.491	4.797	3.439	2.283	λ	1.480	1.503	3.472	2.353
(NW)	(1.04)	(2.92)	(2.23)	(1.20)	(NW)	(1.00)	(2.64)	(2.23)	(1.30)
(Sh)	(1.04)	(3.03)	(2.21)	(1.20)	(Sh)	(1.03)	(2.65)	(2.22)	(1.31)
	RMSE	Adj R^2	χ^2			RMSE	Adj R^2	χ^2	
	0.67	0.73	62.3 [0.18]			0.67	0.73	67.3 [0.09]	
GMM	DOL	SRP_{HML}	MOM	VAL	GMM	DOL	SRP_{NT}	MOM	VAL
b	-0.000	0.008	0.006	0.002	b	0.001	0.077	0.006	0.002
	(-0.09)	(2.49)	(2.41)	(0.74)		(0.36)	(2.65)	(2.56)	(0.58)
λ	1.491	4.797	3.439	2.282	λ	1.480	1.503	3.472	2.546
	(1.06)	(3.07)	(2.24)	(1.23)		(1.03)	(2.75)	(2.24)	(1.30)
		χ^2					χ^2		
		64.8[0.13]					65.4[0.12]		
Panel C: Replacing SRP_{HML} by CAR									
FMB	DOL	CAR	MOM	VAL	GMM	DOL	CAR	MOM	VAL
λ	1.483	4.843	3.442	2.070	b	0.001	0.007	0.007	0.001
(NW)	(1.03)	(2.78)	(2.22)	(1.08)		(0.22)	(2.51)	(2.79)	(0.30)
(Sh)	(1.03)	(2.78)	(2.21)	(1.10)	λ	1.483	4.843	3.442	2.070
						(1.05)	(2.79)	(2.22)	(1.10)
	RMSE	Adj R^2	χ^2				χ^2		
	0.66	0.74	62.0 [0.19]				65.6 [0.12]		

IV.1. Spanning Regressions

Table A9: Other Spanning Regressions

The table presents, in Panels C and D, the results from implementing the spanning regressions using the SRP_{HML} factor (SRP) and the competing factors (f_j), i.e., the 11 HML factors associated with the investment strategies, adding the Dollar factor (DOL) as control. Panel C reports the results from regressing the SRP HML factor on each of the competing factors. Panel D presents the results from regressing each of the competing factors on the SRP HML factor; in the bottom rows of Panel D, we present the GRS-test statistic and the corresponding p -value in square brackets. In Panel E, we replace SRP_{HML} with CAR. In the last column, we report the spanning regression R^2 s. The Newey-West t -statistics are presented in round brackets. The sample period is from February 1998 to December 2021.

	C. SRP on f_j				D. f_j on SRP				E. f_j on CAR		
	α	β_{DOL}	β	$Adj\ R^2$	α	β_{DOL}	β	$Adj\ R^2$	α	β	$Adj\ R^2$
CAR	1.72 (1.65)	0.15 (2.74)	0.63 (14.6)	0.63	0.82 (0.73)	0.05 (0.85)	0.90 (18.9)	0.61	-	-	-
NFA	4.23 (3.23)	-0.01 (-0.12)	0.50 (7.45)	0.29	0.02 (0.02)	0.67 (14.1)	0.32 (7.98)	0.62	-0.33 (-0.24)	0.53 (9.09)	0.32
RR	4.11 (3.54)	0.12 (1.62)	0.52 (8.11)	0.48	-1.92 (-1.44)	0.24 (3.07)	0.74 (11.9)	0.50	-2.41 (-2.21)	0.86 (22.4)	0.66
VRP	4.86 (3.80)	0.24 (3.24)	0.45 (7.88)	0.34	-2.10 (-1.57)	0.16 (2.05)	0.57 (8.44)	0.31	-2.30 (-1.83)	0.56 (9.78)	0.39
VRPU	3.86 (3.38)	0.14 (2.23)	0.59 (10.0)	0.47	-1.22 (-1.06)	0.18 (2.82)	0.65 (10.9)	0.48	-0.76 (-0.61)	0.59 (10.1)	0.41
VRPD	3.78 (3.52)	0.03 (0.45)	0.65 (12.5)	0.57	-1.92 (-1.62)	0.26 (4.08)	0.77 (13.8)	0.62	-1.93 (-1.72)	0.81 (17.3)	0.66
VPUD	3.67 (3.62)	0.02 (0.34)	0.64 (13.8)	0.61	-2.08 (-1.86)	0.25 (3.82)	0.84 (16.6)	0.64	-1.98 (-1.90)	0.85 (18.4)	0.67
MOMS	5.02 (3.80)	0.40 (5.41)	0.01 (0.18)	0.15	3.17 (1.82)	-0.15 (-1.66)	0.02 (0.18)	0.01	4.02 (2.35)	-0.17 (-1.97)	0.03
MOMM	4.54 (3.32)	0.42 (5.67)	0.13 (1.71)	0.19	1.60 (0.94)	-0.26 (-2.93)	0.29 (2.64)	0.06	2.74 (1.60)	0.02 (0.20)	-0.00
MOML	4.69 (3.37)	0.43 (5.53)	0.19 (3.42)	0.20	0.41 (0.24)	-0.32 (-2.85)	0.32 (3.36)	0.08	1.48 (0.81)	0.04 (0.59)	-0.00
VAL	4.49 (3.22)	0.35 (4.13)	0.25 (2.78)	0.19	1.82 (0.95)	0.15 (1.42)	0.32 (2.87)	0.09	1.09 (0.63)	0.41 (5.51)	0.17
SRP	-	-	-	-	-	-	-	-	1.68 (1.54)	0.67 (14.9)	0.61
GRS	—				1.79	2.04					
p -value	—				[0.06]	[0.02]					

V. Three-Pass Inference and Analysis

V.1. Three-Pass Inference

In what follows we briefly present the Risk-Premium Principal Component Analysis (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 (2020b), LP hereafter. The RP-PCA method allows to efficiently recover the latent-factor SDF from the panel of currency portfolios (test assets), which is a key input to achieve robust estimates of candidate factors' risk premia via the three-pass method. We first present the RP-PCA estimator and then the three-pass estimator following closely the notation adopted in Nucera et al. (2023).

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

$$X_{nt} = F_t \psi_n^\top + \epsilon_{nt}, \quad n = 1, \dots, N, \quad t = 1, \dots, T, \quad (\text{V.1})$$

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 $X = F\psi^\top + \epsilon$, 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

$$\Sigma_{\text{RP}} = \frac{1}{T} X^\top X + \omega \bar{X}^\top \bar{X}, \quad (\text{V.2})$$

where $\bar{X}$ 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 PCA, the risk exposures are proportional to the eigenvectors associated with the largest eigenvalues of $\Sigma_{\text{PCA}} = \frac{1}{T} X^\top X - \bar{X}^\top \bar{X}$, 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

$$\psi(\Sigma_F + (1 + \omega)\mu_F^\top \mu_F)\psi^\top + \text{Var}(\epsilon), \quad (\text{V.3})$$

where Σ_F and μ_F denote the covariance matrix and the means of F , respectively. More-

over, applying PCA to Σ_{RP} is equivalent to minimizing jointly the time-series unexplained variation and the cross-sectional pricing errors

$$\min_{\psi, F} \underbrace{\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (X_{nt} - F_t \psi_n^\top)^2}_{\text{TS unexplained variation}} + \omega \underbrace{\frac{1}{N} \sum_{i=1}^N (\bar{X}_n - \bar{F} \psi_n^\top)^2}_{\text{CS pricing error}}, \quad (\text{V.4})$$

where $\bar{F}$ is the vector of factor expected values. From Eqs. (V.2)-(V.4), it is clear that RP-PCA with $\omega = -1$, which forgoes the information in the means, is equivalent to standard PCA.

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 ($\bar{\sigma}_\epsilon^2$). To construct such metrics, call-it *first-pass diagnostics*, one can run a battery of OLS regressions

$$X_{nt} = \alpha_n + \hat{F}_t \psi_n^\top + \epsilon_{nt}, \quad n = 1, \dots, N, \quad t = 1, \dots, T, \quad (\text{V.5})$$

where the intercept α_n captures the magnitude of the asset-specific pricing errors. Then, one can use Eq. (V.5) to compute $\overline{RMS}_\alpha = \sqrt{\hat{\alpha} \hat{\alpha}^\top / N}$, and $\bar{\sigma}_\epsilon^2 = \frac{1}{N} \sum_{n=1}^N [\text{Var}(\hat{\epsilon}_n) / \text{Var}(X_n)]$ 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, $\bar{X}_n = \hat{\psi}_n \gamma^\top + a_n$, for $n = 1, \dots, N$, where γ is the $1 \times K$ vector of latent factors’ prices of risk, and the R-squared values (R^2).

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. (V.1) 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

$$\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}, \quad n = 1, \dots, N, \quad t = 1, \dots, T, \quad (\text{V.6})$$

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 $k = 1, \dots, K$, 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,

$$\bar{X}_n = \hat{\psi}_n \gamma^\top + a_n, \quad n = 1, \dots, N, \quad (\text{V.7})$$

where γ is the $1 \times K$ vector of the latent factor prices of risk.³⁰

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

$$g_t^\iota = \hat{F}_t^\iota \eta^\top + u_t, \quad (\text{V.8})$$

where η is the $1 \times K$ vector collecting the loadings of the candidate factor on the K latent factors. Then, using the estimated η -exposures, one implements

$$\hat{\lambda}_g = \hat{\gamma} \hat{\eta}^\top, \quad (\text{V.9})$$

$$\hat{g}_t = \hat{F}_t \hat{\eta}^\top, \quad (\text{V.10})$$

and obtains the *price of risk* of the candidate factor, $\hat{\lambda}_g$, and the *cleaned return-based* candidate factor, $\hat{g}_t$ (i.e., the nontradable factor after the removal of measurement error, u_t , and converted into a tradable return-based factor).

V.2. Three-Pass Analysis

We first perform the three-pass analysis using the full cross-section consisting of the 60 portfolio returns, thus including the 5 SRP portfolios. We then repeat the analysis by excluding the SRP portfolios, to better gauge the strength of the SRP portfolios. To

³⁰Note 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).

conclude the three-pass analysis, we present two additional exercises. First, we assess the returns from combining SRP_{HML} with the other strategy factors, both in their noisy and de-noised versions, further complementing what we have done in factor spanning regressions. Second, we provide robust estimates of the risk premium of the SRP nontradable factor, and compare with those of other nontradable measures.

V.2.1. Baseline Analysis

In what follows we report the three-pass estimates using the full cross-section of test assets, thus including also SRP portfolios.

Latent-Factor SDF. Table 6 presents the statistics of the first nine extracted latent factors and the economic diagnostics of the associated currency SDF.³¹ We employ a total of 60 portfolios constructed based on the 12 sorting variables ($12 \times 5 = 60$). Following Nucera, Sarno, and Zinna (2023), we set $\omega = 20$ as the baseline RP-weight, which seems to be a reasonable choice also in our sample.³²

By inspecting Table 6, 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). Moreover, its estimated mean (risk premium) is statistically insignificantly different from zero, which suggests that F_1 is essentially a level factor that captures mainly time series variation in the test assets.³³ Second, factors F_2 to F_4 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 four-factor model achieves an R^2 above 98%, and the maximal Sharpe ratio (mSR) of the tangency portfolio spanned by these four factors is 1.33 (annualized). Third, the role of F_5 , which also has a positive and statistically significant risk premium, is less clearcut, leading to a modest increase in the mSR and a negligible increase in the cross-sectional R^2 , but its inclusion in the SDF helps improve the model's pricing accuracy (further evidence on this later on).³⁴

To gauge further indications on the optimal size of the SDF, we recur to the tests of Onatski (2010) and Giglio and Xiu (2021). These tests exploit the information in the

³¹We base the three-pass empirical analysis on rotated, orthogonalized latent factors with positive means.

³²We present in the Internet Appendix, Table A10, 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.

³³Nucera et al. (2023) 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, which helps achieve full spanning.

³⁴The remaining factors display low 'signal strenghts', and hence appear to be of second order importance. This will become more evident later when we turn to the HML factor risk-premium estimates. Moreover, by adding too many factors in the model on the backdrop of an already accurate cross-sectional fit, one incurs the risk of overfitting, which can manifest especially in out-of-sample settings (the short time span of option data currently prevents a sound out-of-sample analysis).

latent factor eigenvalues to determine the optimal number of factors. Notably, both tests point to three factors. However, these results need to be taken with caution, because in finite samples these tests tend to underestimate the true number of factors (see, e.g., Giglio and Xiu, 2021; Nucera, Sarno, and Zinna, 2023). Thus, three should be regarded as the minimum number of factors entering the SDF. In general, it is important to complement the information one obtains from the test results with other criteria, such as the economic diagnostics presented in Table 6. 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 five-factor model, only 1 out of 60 portfolios have statistically significant average pricing errors at the 5% significance level, whereas this number rises to 6 when we use a more parsimonious four-factor model. As a result, a five-factor model seems a more adequate choice than a four-factor model.³⁵

Taken together, these multiple pieces of evidence suggest that the currency SDF consists of five factors. 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 7 reports the risk exposures, η , of the 12 HML factors to the first six latent factors, together with the explained variations for models including an increasing number of factors.³⁶ Aside from helping interpret the sources of risks priced in the SDF, we note that the η s are important objects in the three-pass procedure, as they map the latent factor risk premia onto the candidate factor risk premia.³⁷ At the same time, the R^2 s 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, 2022).

The interpretation of the first four factors is clearcut. While F_1 is close to a level “Dollar factor” (individual portfolios have similar positive risk exposures), the remaining factors are clearly slope factors. Specifically, F_2 is a “Carry” factor, F_3 is a “Momentum” factor, and F_4 is “long Value short (long-term) Momentum” factor. This evidence is largely in line with the one provided by Nucera, Sarno, and Zinna (2023), despite the

³⁵The 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 follow Nucera et al. (2023) and 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. As a result, we conclude that a five-factor model is statistically consistent with full spanning.

³⁶We present the evidence for the first nine factors in Table A11 in the Internet Appendix.

³⁷In Figures A2 and A3 we present test assets' risk exposures and explained variations by latent factor. Note that the difference in the strategy corner portfolio factor loadings extracted in the first pass ($\Phi_{P5} - \Phi_{P1}$) is close to, and hence provides similar information to, the η -exposure of the strategy HML factor to the selected latent factor. This is because risk exposures estimated via the RP-PCA factor model and OLS regressions can deviate, unless the OLS data are transformed to account for the pricing errors. (e.g., see Lettau and Pelger, 2020b; Nucera, Sarno, and Zinna, 2023).

two studies focus on substantially different samples. However, the inclusion of option strategies helps us refine the factors' interpretation.

F_2 is a very important factor not only for Carry and RR, but also for currency strategies that reflect downside (VRPD) and asymmetry/skewness risk premia (VRPUD and SRP_{HML}) in currency returns. While both option-based strategies of VRP and VRPU are also significantly exposed to F_2 , their η_2 -estimates are small. Moreover, the inclusion of F_2 leads to a more contained increase in their R^2 s. The risks captured by F_2 are much less relevant for VAL and MOML, and are essentially negligible for MOMM and MOMS. 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). It is also apparent that there is a positive relationship between SRP_{HML} and F_3 , and a negative one between VRP and F_4 . Unlike the factors ordered before, F_5 does not display any clearcut interpretation (though is somewhat more relevant for MOMS, VRP, and NFA).³⁸

Of particular relevance for this study is the fact that SRP_{HML} emerges as the only factor displaying positive and statistically significant exposures to all of the first three factors, thus being a procyclical factor with respect to these sources of risk. Indeed, notwithstanding the exact size of the currency SDF, these factors undoubtedly enter the currency SDF, and hence represent the main sources of priced currency risk. It follows that SRP_{HML} should be regarded as a currency pricing risk factor, lending support to our prior two-pass and spanning evidence. 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 8 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). Using a five-factor model, eight of the nine HML factors with significant average returns also have significant risk-premium estimates (the only exception being VRPD). Specifically, the SRP_{HML} risk-premium estimate is close to the model-free estimate given by its mean (4.79% vs. 5.64%). This is true for most of the HML factors. In fact, the difference between the three-pass estimate and the model-free one is marginally statistically significant only for VRPU (using a six-factor model the difference becomes insignificant). This evidence, taken together, suggests that the pricing performance of the five-factor model is accurate.

It is then 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 risk premia. However, this

³⁸The remaining factors tend to have smaller signal-to-noise ratios (due to lower time-series strengths and risk premia), and hence are inherently less relevant. Most likely they reflect risks that are unpriced, or only weekly priced in few strategies, being relevant only for some portfolios. For example, F_6 mainly relates to VRPU, F_7 to MOMS, F_8 to VAL, and F_9 to SRP. Later on, we will show their impact on the HML factor risk-premium estimates, to further assess their relevance.

is clearly not the case for MOM 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 VRPUD).

When the third factor is added to the model, the premia of MOM strategies rise substantially (especially those of MOMM and MOML), consistent with F_3 's interpretation as a momentum-like factor. Moreover, the estimate of the SRP_{HML} risk premium and its Sharpe ratio rise, moving closer to their observed counterparts. Thus, F_3 captures the positive link between SRP_{HML} and MOM strategies, and yet has no impact on the CAR risk premium (its premium remains unchanged). In this sense, F_3 captures the disconnect between CAR and SRP. We notice also a substantial fall in the estimate of the VAL risk premium, when moving from a two- to a three-factor model.

Next, F_4 increases substantially the risk-premium estimates of VAL and MOMS (by roughly 3%), while reducing those of MOMM and MOML. We also observe a slight increase in the SRP_{HML} and CAR risk premia (VRPU shows a more substantial increase). As we add F_5 to the model, the risk premia of most strategies drop, with the exception of the MOM and VRPU strategies. Thus, F_5 is a countercyclical source of risk for SRP_{HML} , unlike the first four factors.³⁹

De-Noised Factors. To complement the above analysis, we visually inspect the behavior of the de-noised factors. A de-noised factor is the original candidate factor cleaned from measurement errors (and/or unpriced risks in the case of tradable candidate factors), by projecting the factor onto the space of the latent factors extracted via RP-PCA, using the η -exposure estimates. Put simply, 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 5 shows the cumulative returns of the de-noised HML factors using models of increasing dimension, whereby factors are added successively one by one. In this way, we can visually gauge the marginal contribution of each latent factor in driving the evolutions and levels of the de-noised factor of interest. To be more specific, the larger the absolute distance between the two de-noised versions of the same HML factor, the higher the absolute relevance of the extra latent factor(s). The sign of the wedge is informative about the procyclicality of the extra factor(s) for that candidate factor.

To start with, we look at de-noised SRP_{HML} (top left panel of Figure 5). First, it clearly emerges that F_2 accounts for most of the SRP_{HML} risk premium (dashed red line), while F_1 exerts a much smaller effect (solid black line), consistently with it being a strong time-series factor and hence with low Sharpe ratio and risk premium. By adding F_3 , de-noised SRP_{HML} yields higher returns. But this can hardly be visualized as its time

³⁹By including additional factors, the risk-premium estimates are rather stable for most strategies, with only few notable exceptions. For example, F_6 and F_7 reduce, respectively, the premia of VRPU and MOMS, while F_9 raises those of SRP and VRPU. This evidence is not surprising, for two main reasons. These factors being ordered last tend to have lower time-series strengths; this can be seen in their diminishing contributions in lowering the idiosyncratic variation (Table 6). While these factors display nonnegligible risk premia, they are unlikely to be systematic sources of priced risk.

series is overshadowed by de-noised versions obtained using more factors. This is exactly because these other factors add or detract little to the SRP risk-premium estimate.⁴⁰ Thus, this evidence confirms that F_2 and F_3 , which are two priced sources of currency risk, drive the bulk of SRP_{HML} variation and risk premia.

It is useful to contrast the SRP evidence with the other de-noised factors. For instance, it is evident that the de-noised CAR is almost entirely driven by F_2 . Importantly, F_2 is the dominant factor not only for SRP and CAR, but also for many other currency strategies (evidently excluding MOM strategies). The remaining pricing factors (F_3 to F_5) are particularly relevant for trend strategies (i.e., conditioning on past returns), albeit with some notable differences. For example, while F_3 is the main source of procyclical risk for MOMM and MOML, both F_3 and F_4 matter for MOMS.

Turning to the factors' evolutions, there is increasing evidence that the performance of many currency investment strategies has dropped with the onset the GFC and the consequent reductions in interest rates (see, e.g., Andrews et al., 2023; Lilley and Rinaldi, 2020; Fan et al., 2022). This reduction in returns is also evident in most of the 12 currency strategies we consider; the SRP HML factor is no exception in this regard, despite its high risk premium and Sharpe ratio over the full sample. To this end, the three-pass procedure provides a valuable means to determine which source of (priced) risk, or latent factor, is responsible for such observed flattening in currency returns post GFC.

Figure A4, in the Internet Appendix, shows that, among the relevant factors (F_1 to F_5), all factors but F_4 – which increases almost steadily throughout the sample — display some reduction in returns with the onset of the GFC and in the subsequent years. For instance, both the cumulative returns of F_2 and F_3 flatten post GFC, but F_2 does so much less than F_3 . Then, the η -exposures ultimately map such effects onto the de-noised strategy returns. For example, Figure 5 shows that the SRP HML factor is affected by the return drop in both F_2 and F_3 , while the reduction in the CAR returns is driven only by F_2 . Clearly, F_3 also accounts for the lower post-GFC performance of all MOM strategies, but MOMS benefits from the good performance of F_4 . Of course F_4 has a pronounced effect also on the VAL strategy.

V.2.2. *Ex-SRP Portfolios Analysis*

So far, we have carried out the RP-PCA baseline three-pass analysis based on 60 portfolios that include the 5 SRP portfolios. It is, however, useful to repeat the analysis by excluding the SRP portfolios from the cross-section of test assets. By doing so, we can try to better (i) isolate the contribution of SRP to the currency latent-factor SDF (and mean-variance efficient frontier) and, relatedly, (ii) shed additional light on the strength of the SRP HML factor, by assessing the accuracy of the recovery of its risk premium in a broad cross-section of currency portfolio returns which does not include SRP portfolios.

⁴⁰The only factor that shows a distinct, albeit tiny, contribution when compared to F_2 and F_3 , is F_9 (blue line).

Stability of the Latent-Factor SDF. To start with, we assess the impact of the SRP strategy on the currency SDF. Table A13 shows that the maximal Sharpe ratio of the tangency portfolio constructed via RP-PCA drops when SRP portfolios are excluded from the test assets. This holds regardless of the exact number of factors employed to span the mean-variance frontier. This is because the factors estimated from the ex-SRP sample display lower risk premia and Sharpe ratios.⁴¹ Therefore, the inclusion of SRP portfolios turns out to be important to achieve a more precise recovery of the currency SDF. Put simply, by investing in the SRP portfolios, one moves closer to the currency mean-variance efficient frontier.

Next, we inspect the stability of the factor structure. The statistical tests still select three as the optimal number of latent factors entering the SDF. The economic diagnostic criteria behave qualitatively, and in most cases also quantitatively, very similarly to the baseline (see Table 6). The interpretation of the first latent factors also remains essentially unchanged (Table A14). In particular, SRP_{HML} is still positively exposed to the first three factors entering the SDF, and F_2 still accounts for the bulk of the SRP_{HML} variation.

Therefore, this additional analysis lends support to our previous two-pass asset pricing results. The SRP strategy is not entirely subsumed by the other investment strategies, as one achieves a better risk-return trade-off by investing in SRP portfolios. At the same time, SRP_{HML} appears to be a strong currency pricing factor. Indeed, the bulk of the SRP_{HML} information is priced in the other currency investment strategies, which is consistent with a strong factor interpretation.

Recovery of the SRP Risk Premium. In what follows, we try to shed further light on the strength of the SRP factor, by carrying an additional exercise. That is, we assess the accuracy of the three-pass estimate of the SRP risk premium, when dropping the SRP portfolios from the sample of test assets. If the recovery of the risk premium remains accurate also in this cross section, the case of SRP being a strong pricing factor would become even more compelling. This is because in this case we can rule out that the recovery of the SRP risk premium hinges upon the inclusion of the SRP portfolios, which would be symptomatic of a weak(er) factor. Recall that a factor is not strong or weak in absolute terms, but relative to the cross-section of test assets used by the researcher (Giglio et al., 2022). Thus, by focusing on the ex-SRP sample (i.e. $N = 55$), we make sure that the result is not affected anyhow by the inclusion of the SRP portfolios.

A useful metric to look at to determine the accuracy of the estimate is the pricing error – measured as the absolute difference between the factor average return and the risk-premium three-pass estimate. That is, the larger the pricing error, the weaker the factor is. We find that the recovery of the SRP risk premium remains very accurate also when dropping the SRP portfolios (Table A15). This holds regardless of the SDF dimension, as long as the model includes more than three factors. In fact, we cannot reject that

⁴¹Specifically, if we look at the first five factors (the ones entering the optimal SDF), we mainly notice that the average return of F_2 is less precisely estimated, and the one of F_5 is no longer statistically significant. Among the remaining factors, F_7 remains the only factor with significant average returns (and at the 5% level).

the average pricing errors are zero using any of the multifactor models. Specifically, the estimate of the SRP risk premium is 3.20% using a two-factor model, and rises to 4.05% using a three-factor model (the baseline estimates were 3.88% and 4.78%, respectively). Consistent with the signs of the η -exposures, the estimates slightly reduce by adding more factors, mainly due to the effect of F_5 . But the drop is economically small, being of the order of 50 bps.⁴² We find similar evidence by focusing on the Sharpe ratios of de-noised SRP factors.⁴³

Next, we assess if any of the other strategies is particularly important to the recovery of the SRP risk premium by excluding both the SRP portfolios and one by one the other strategies from the test assets; thus, we rely on $N = 50$ cross-sections.⁴⁴ If this turns out to be the case, then the SRP factor would be relatively weak (being a risk factor only for a subset of the strategies). We find that, using five-factor models, the risk-premium estimates range from a minimum of 3.36% to a maximum of 4.05% (Panel A, Table A16). Not surprising, we obtain the largest pricing errors by dropping both CAR and SRP portfolios, which corroborates the close link between the two strategies documented earlier. Nevertheless, none of the strategies turns out to be crucial for the recovery of the SRP risk premium.

This additional analysis convincingly shows that SRP_{HML} is not only a high risk-premium factor but also a rather strong factor, as its information is priced in many strategies and hence is reflected in the SDF, regardless of whether SRP portfolios are included in the sample of test assets. SRP_{HML} behaves very much like CAR HML and, indeed, the two appear closely linked together. To the contrary, VAL also displays a relatively high risk premium, but it appears to be a much weaker factor, as the recovery of its risk premium very much hinges upon the use of VAL portfolios as test assets (to a large extent, a similar argument applies to MOMS).⁴⁵ This is because RP-PCA is more likely to detect weak factors if they have high risk premia, but cannot detect weak factors in general (Giglio, Xiu, and Zhang, 2022). Indeed, latent factors estimated with RP-PCA

⁴²Turning to the other factors, by excluding the SRP portfolios, the main difference seems to pertain to F_9 , which again appears to be a weak factor tightly linked to SRP_{HML} . This additional analysis shows that its detection relies on the use of SRP portfolios.

⁴³For comparison, we do repeat the same exercise for VAL and CAR (not reported). We find that VAL appears to be a much weaker factor than SRP, as the use of the VAL portfolios in the set of test assets is key to recover the VAL risk premium; in fact, by excluding the VAL portfolios, its risk-premium estimate reaches a maximum of 2% using a two-factor SDF, and is not statistically significant using larger models. By contrast, CAR seems to behave very much like SRP, given that we can estimate accurately its risk premium even by excluding the CAR portfolios from the cross-section.

⁴⁴Ideally, we would have preformed the analysis as in the two-pass analysis, i.e., for smaller cross-sections, to better link group of strategies to the SRP factor. However, the asymptotic properties of the three-pass estimator have been assessed only in finite samples with $N \geq 50$. Thus, we carry out the analysis for $N = 50$, by excluding no more than two strategies at a time.

⁴⁵To be precise, the Dollar factor – which is tightly linked with F_1 – is the only strong factor, in terms of time-series strength, driving currency strategy portfolios. The remaining factors are weak but with different strengths. Thus, although also CAR and SRP are weak factors, they appear to be much stronger factors than VAL, for example.

heavily weigh on the high risk-premium (or Sharpe ratio) portfolios, or strategies. Thus, if a HML factor has high risk premium but is weak (being disconnected from the other strategies), one can only hope to recover its risk premium if its portfolios are used as test assets.⁴⁶

V.2.3. Additional Three-Pass Analysis

Strategy Combos. In what follows, we assess the pairwise combinations of each of the 11 investment strategies with SRP. Such types of simple equally-weighted strategy combos are widely traded by sophisticated investors (see, e.g., Asness, Moskowitz, and Pedersen, 2013). Moreover, they provide a simple and yet convenient way to zoom into the relationship between SRP and the other popular currency strategies. Intuitively, this analysis complements the Sharpe ratio tests performed in Table 5. The results are clearcut (Panel A.I, Table A17). All combos display higher Sharpe ratios than the original strategy combined with SRP_{HML} . There are, however, two cases of particular interest. First, by combining SRP with CAR, the benefits are contained in comparison with the other combos. This is largely expected, due to the close link between the two strategies. Second, the gain is instead large when combining SRP with MOMS, in light of their weak correlation, which results in larger diversification benefits. Indeed, we are combining a strategy with negative skew (SRP) with one with positive skew (MOMS).⁴⁷

Finally, we revisit the pairwise strategy combos through the lens of the three-pass estimator. We do so by combining the de-noised factors, instead of the noisy factors (Panel B.I, Table A17). The de-noised factors are obtained using the baseline sample and RP-weight ($N = 60$ and $\omega = 20$) using models of the same but increasing dimension.⁴⁸ We find that all de-noised combo strategies yield statistically significant returns, by using multifactor models. However, both the risk premia and Sharpe ratios do not increase monotonically as additional factors are considered. For instance, the MOMM and MOML combos reach the highest Sharpe ratios using the three-factor model, while MOMS using a five-factor model. Notably, for most strategies, the Sharpe ratios peak using rather parsimonious models (less than the optimal number of factors entering the SDF), so that only in very few cases the combo performances improve by including factors ordered after the fifth (i.e., non-relevant factors that are excluded from the SDF). This lends further support to the choice of excluding factors after the fifth from the SDF. Moreover, for almost all strategies, there is at least one de-noised combo that exceeds the noised combo (with the exception of CAR). For example, the de-noised MOMS combo reaches a

⁴⁶Indeed, Giglio, Xiu, and Zhang (2022) theoretically show that, if the signal-to-noise ratio is too low, the recovery is not guaranteed also in this case. Alternatively, one needs to adapt the cross-section of test assets to enhance the signal-to-noisy ratio.

⁴⁷The gains are also large by combining SRP with VAL, but the combo Sharpe ratio is below the Sharpe ratio of SRP.

⁴⁸To be clear, these combos are tradable but not in real time, given that the latent factors and the loadings are constructed in-sample. Yet, they could be reconstructed in real time, e.g., through recursive estimation of the RP-PCA model.

remarkably high Sharpe ratio of 1.28 using a five factor model (against 0.86 of the noisy combo, and same skewness, 0.28).

To visually inspect the cumulative returns of the combo strategies, Figure A5 shows some selected combos that exemplify the types of behavior of the 11 strategies. We construct the de-noised combos using the five-factor model (thus some other de-noised versions could perform better depending on the strategy). It is apparent that there is essentially no gain in profitability by combining SRP and CAR strategies, while the gains are large for the remaining strategies. VRP combo works better using the noisy factors than the de-noised factors (at least based on the five-factor model), while MOMS using the de-noised combo. Regardless of whether de-noised or not, the VAL combo displays a return that is consistently high both before (when SRP does well) and after (when VAL does well) the GFC.

Nontradable Factor(s). 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 clearly connect with specific sources of 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, 2023). 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 A18, SRPNT panel, shows the three-pass estimates of SRP_{NT} , using models including up to nine factors (recall that the optimal SDF consists of five). The estimates closely resemble the ones of the tradable counterpart, SRP_{HML} , both qualitatively and quantitatively. In fact, SRP_{NT} risk-premium estimates and Sharpe ratios increase as we add factors successively to the SDF (up to the fourth), and drop somewhat as we also include the fifth factor, which was a countercyclical source of risk also for SRP_{HML} . This is because the SRP_{NT} η -exposures to the first four latent factors are positive and statistically significant (except for η_4), while the η_5 estimate is negative and significant. Most of the variation in SRP_{NT} is explained by F_2 , with a non-negligible contribution of F_5 .⁴⁹ Importantly, the risk-premium estimates are statistically significant, regardless of the exact number of factors included in the SDF (at the 1% using up to four factors, and at the 5% level using a five-factor model). The Sharpe ratios are reasonably high, being only slightly lower than the tradable factor estimates (reaching a peak of 0.87 using the four-factor model, and dropping to 0.61 moving to the five-factor model).

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 also apparent the close evolutions of the de-noised SRP_{NT} and SRP_{HML} factors (Figure 5). Moreover, we find that the five-factor model risk-premium estimates

⁴⁹ SRP_{NT} is also exposed to F_9 , which we know from before that, albeit not being a relevant pricing factor, is also closely linked to SRP_{HML} .

remain rather stable as we drop the SRP portfolios and, one by one, those of any other strategy from the test assets (Table A16, Panel B), thus resting on $N = 50$ cross-sections. Taken together, this analysis allows us to rule out that the two-pass analysis results on SRPNT were due to either measurement error in the factor and/or to the potential omission of relevant control factors in the SDF. Moreover, also through the lenses of the three-pass method, the tradable and nontradable factors seem to be closely related. This suggests that SRP_{HML} is an accurate measure of the predictability in currency excess returns generated by skewness risk premia. This evidence in turn validates our choice to carry out the main asset pricing analysis using the tradable factor SRP_{HML} , exploiting in full the benefits of working with tradable factors.

To complete the analysis, we present in Table A18 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.⁵⁰ 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. However, none of the risk-premium estimates are statistically significant, based on the optimal five-factor model. This is in stark contrast with SRP_{NT} , whose risk-premium estimates are strongly significant, regardless of the dimension of the SDF.

Specifically, most factors are exposed to only few sources of priced currency risk, mainly to F_2 . But their η_2 estimates are much smaller in absolute terms than that of SRP_{NT} (nontradable factors are standardized so that the η -exposures are directly comparable). Moreover, unlike SRP_{NT} , none of the nontradable factors display both η_3 and η_4 estimates of the same sign of η_2 . Thus, not only F_5 , but also other factors dampen the effect of F_2 on the nontradable factor risk-premium estimates, albeit to different extent across factors. This can be easily visualized in Figure A6, by looking at the cumulative returns of the de-noised nontradable factors, obtained by varying the SDF dimension.

Of particular interest is EQTAIL given that is a measure of equity tail risk, which has been shown to be relevant for currency returns (Fan, Londono, and Xiao, 2022). Specifically, we find that EQTAIL is negatively exposed to the first two factors, so that its risk premium is statistically significant. But it is positively exposed to F_3 and F_5 ,

⁵⁰Fan, 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.

implying a smaller, and non-significant, absolute risk premium estimate based on larger models (including the optimal five-factor model). In contrast, the two-factor model risk-premium estimate represents a lower bound, in absolute terms, for SRP_{NT} .⁵¹

⁵¹GIV single out for two main reasons. First, its absolute risk-premium point estimates peak using a five factor model. Second, based on this model, the de-noised factor behaves quite similarly pre- and post-GFC, unlike most of the other nontradable factors. Its Sharpe ratio is economically large. Nevertheless, its premium are very poorly estimated in our sample.

Table A10: 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, $k = 1, 2, \dots, 9$. 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, $\bar{\sigma}_\epsilon^2 = \frac{1}{N} \sum_{n=1}^N [Var(\hat{\epsilon}_n)/Var(X_n)]$; 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 $n = 1, \dots, N$ test assets, and $t = 1, \dots, T$ months. *II.b: 2P* presents the second-pass diagnostics: the mean absolute errors (MAE) of the cross-sectional regression, $\bar{X}_n = \hat{\psi}_n\gamma^\top + a_n$, for $n = 1, \dots, N$, 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 $\hat{b}_{MV,k} = \mu_{F,k}/\sigma_{F,k}^2$, with $\mu_{F,k}$ and $\sigma_{F,k}^2$ 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	
	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\bar{\sigma}_\epsilon^2$	$\overline{RMS}_\alpha$	MAE	$R^2(\%)$	SR	ΔSR
$\omega = -1$										
F_1	12.23	0.22	0.03	$\varphi(F_1)$	20.89	1.17	0.95	34.53	0.22	.
F_2	5.13*	0.38	0.23	$\varphi(F_{1-2})$	16.00	0.96	0.79	45.26	0.44	0.21
F_3	3.47*	0.37	0.32	$\varphi(F_{1-3})$	13.65	0.85	0.70	57.15	0.57	0.13
F_4	0.96	0.14	0.16	$\varphi(F_{1-4})$	12.35	0.84	0.69	58.04	0.59	0.02
F_5	2.35*	0.38	0.52	$\varphi(F_{1-5})$	11.37	0.79	0.62	63.36	0.70	0.11
F_6	1.77	0.31	0.46	$\varphi(F_{1-6})$	10.53	0.75	0.58	66.45	0.77	0.07
F_7	2.23**	0.45	0.76	$\varphi(F_{1-7})$	9.89	0.70	0.52	71.44	0.89	0.12
F_8	0.13	0.03	0.05	$\varphi(F_{1-8})$	9.28	0.70	0.52	71.48	0.89	0.00
F_9	0.39	0.08	0.15	$\varphi(F_{1-9})$	8.70	0.69	0.51	71.57	0.89	0.00
$\omega = 10$										
F_1	12.53	0.23	0.03	$\varphi(F_1)$	20.90	1.17	0.91	50.90	0.23	.
F_2	6.81**	0.51	0.32	$\varphi(F_{1-2})$	16.05	0.94	0.60	68.18	0.56	0.33
F_3	4.91**	0.53	0.48	$\varphi(F_{1-3})$	13.70	0.84	0.45	82.55	0.77	0.21
F_4	4.33***	0.67	0.86	$\varphi(F_{1-4})$	12.51	0.79	0.32	91.98	1.02	0.25
F_5	4.65***	0.77	1.07	$\varphi(F_{1-5})$	11.50	0.67	0.21	95.82	1.28	0.26
F_6	2.34*	0.41	0.61	$\varphi(F_{1-6})$	10.65	0.63	0.19	96.69	1.35	0.07
F_7	3.27***	0.66	1.09	$\varphi(F_{1-7})$	9.98	0.54	0.14	98.17	1.50	0.15
F_8	0.12	0.02	0.04	$\varphi(F_{1-8})$	9.37	0.54	0.14	98.17	1.50	0.00
F_9	1.64*	0.36	0.64	$\varphi(F_{1-9})$	8.81	0.51	0.13	98.45	1.54	0.04
$\omega = 50$										
F_1	13.39	0.25	0.04	$\varphi(F_1)$	20.94	1.17	0.76	82.47	0.25	.
F_2	8.72***	0.77	0.57	$\varphi(F_{1-2})$	16.41	1.00	0.22	96.21	0.81	0.56
F_3	6.31***	0.70	0.64	$\varphi(F_{1-3})$	13.93	0.88	0.12	98.65	1.07	0.26
F_4	6.21***	1.01	1.38	$\varphi(F_{1-4})$	12.83	0.65	0.05	99.78	1.47	0.41
F_5	2.46*	0.36	0.44	$\varphi(F_{1-5})$	11.61	0.60	0.04	99.82	1.52	0.04
F_6	2.17*	0.38	0.55	$\varphi(F_{1-6})$	10.74	0.56	0.04	99.86	1.56	0.05
F_7	2.77***	0.54	0.86	$\varphi(F_{1-7})$	10.03	0.48	0.03	99.91	1.65	0.09
F_8	0.14	0.03	0.05	$\varphi(F_{1-8})$	9.42	0.48	0.03	99.92	1.65	0.00
F_9	1.97**	0.43	0.78	$\varphi(F_{1-9})$	8.86	0.43	0.03	99.94	1.71	0.05

Table A11: Risk Exposures of Tradable Factors: Using Up to 9 Latent Factors

The table presents the 12 tradable, HML factors' exposures to the latent factors (A.I: Risk Exposure, η_{F_k}) and the explained variations (A.II: Explained Variation, $R^2_{F_{1-k}}$) obtained from the spanning regressions including an increasing number of factors, $k = 1, \dots, K$. We report the exposures to the first nine extracted, orthogonalized latent factors (i.e., $K = 9$). In Panel A, latent factors are extracted by applying rpPCA (with RP-weight $\omega = 20$) to the baseline sample of $N = 60$ portfolios obtained from the 12 investment strategies. In Panel B, latent factors are extracted from $N = 55$ portfolios, by excluding the SRP portfolios from the baseline sample. Based on Newey-West standard errors, ***, **, * denote statistical significance at the 1-, 5- and 10-percent levels, respectively.

Panel A: Baseline Sample (60 Test Assets)											
A.I: Risk Exposures						A.II: Explained Variation					
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_1}$	$R^2_{F_{1-9}}$
SRP	0.05***	0.41***	0.16***	0.05	-0.08	-0.03	0.04	0.12**	0.30***	17.84	77.12
CAR	0.06***	0.53***	0.00	0.09*	-0.19***	-0.04	0.02	-0.14***	-0.06	14.10	85.29
RR	0.07***	0.49***	-0.25***	-0.06	-0.11***	-0.20***	-0.17***	-0.13*	0.09*	21.79	84.63
NFA	0.10***	0.17***	0.02	0.24***	-0.29***	-0.25***	0.03	-0.25***	0.09*	57.00	78.32
MOMS	-0.02	-0.06	0.45***	0.51***	0.25***	0.13*	-0.63***	0.10*	0.17***	1.68	53.33
MOMM	-0.02	0.10	0.76***	-0.36***	0.12	-0.11*	0.23***	0.13**	-0.28***	1.17	71.80
MOML	-0.03*	0.10*	0.75***	-0.52***	0.09**	0.12*	0.12*	-0.25***	-0.20***	2.29	77.18
VAL	0.03***	0.26***	-0.37***	0.57***	-0.01	0.43***	0.04	0.36***	-0.47***	5.36	82.05
VRP	0.05***	0.34***	-0.11**	-0.41***	-0.23***	0.50***	-0.04	0.11**	-0.04	13.26	68.27
VRPD	0.08***	0.47***	-0.05*	-0.16**	-0.27***	0.23***	-0.12***	0.04	0.06	26.93	82.15
VRPU	0.06***	0.35***	0.07	0.19***	0.02	-0.54***	-0.07	-0.07	0.40***	19.14	89.39
VRPUD	0.08***	0.50***	0.00	-0.05	-0.22*	-0.05	-0.24***	-0.07	0.22***	26.57	75.31
										83.45	88.40
										83.44	88.54
										83.44	89.98

Panel B: Ex-SRP Sample (55 Test Assets)											
B.I: Risk Exposures						B.II: Explained Variation					
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_1}$	$R^2_{F_{1-9}}$
SRP	0.06***	0.39***	0.16***	-0.01	-0.12**	-0.06	-0.09	-0.01	0.01	17.64	70.08
CAR	0.06***	0.55***	0.05**	0.11**	-0.15***	-0.06	0.04	0.15***	-0.29***	14.02	84.77
RR	0.08***	0.52***	-0.21***	-0.05	-0.08**	-0.18***	-0.20***	0.22***	-0.20***	21.76	84.77
NFA	0.11***	0.18***	0.04	0.27***	-0.26***	-0.29***	-0.03	0.25***	0.13**	56.96	79.71
MOMS	-0.02	-0.09*	0.44***	0.46***	0.38***	0.19***	-0.57***	-0.06	0.12	1.71	57.48
MOMM	-0.02	0.07	0.78***	-0.35***	0.09	-0.12*	0.25***	-0.27***	-0.04	1.20	77.85
MOML	-0.03*	0.08	0.77***	-0.49***	0.05	0.12***	0.21***	0.13**	-0.11**	2.33	81.72
VAL	0.04***	0.29***	-0.35***	0.55***	0.01	0.43***	0.11	-0.60***	-0.04	5.38	68.70
VRP	0.05***	0.36***	-0.07*	-0.36***	0.49***	0.49***	-0.06	0.05	-0.22***	13.24	83.38
VRPD	0.08***	0.48***	-0.00	-0.12*	-0.30***	0.22***	-0.15***	0.03	-0.14***	26.84	89.50
VRPU	0.06***	0.35***	0.10**	0.16***	0.09*	-0.55***	-0.16***	0.15***	0.40***	19.07	74.72
VRPUD	0.08***	0.52***	0.05*	-0.01	-0.19***	-0.04	-0.28***	0.16***	0.07	26.47	86.26
										84.28	89.00
										84.28	89.80
										84.28	89.91

Table A12: Risk Premia of Tradable Factors: Using Up to 9 Latent Factors

The table presents the rpPCA three-pass risk-premium estimates for the HML tradable factors associated with the 12 currency investment strategies using larger SDFs, including up to nine latent factors. Specifically, we implement rpPCA with baseline RP-weight $\omega = 20$, using models of different dimension, denoted by SDFs with increasing number of factors, i.e., $\varphi(F_{1-k})$ with $k = 2, \dots, 9$. For each model, we report the risk-premium estimates (λ_g); the asymptotic standard errors (se); and the annualized Sharpe ratios (SR) associated with the projected factor, i.e., the de-noised counterpart to the original candidate factor. $***, **, *$ denote significance, respectively, at the 1-, 5- and 10-percent levels. In Panel A, latent factors are extracted by applying rpPCA (with RP-weight $\omega = 20$) to the baseline sample of $N = 60$ portfolios obtained from the 12 investment strategies. In Panel B, latent factors are extracted from $N = 55$ portfolios, by excluding the SRP portfolios from the baseline sample.

Panel A: Baseline Sample (60 Test Assets)														
Model Free			$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$		
μ_g	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g
SRP	5.64***	(1.65)	3.88***	(1.31)	0.65	4.78***	(1.39)	0.78	5.07***	(1.40)	0.82	4.79***	(1.41)	0.77
CAR	5.88***	(1.79)	4.85***	(1.61)	0.66	4.85***	(1.63)	0.66	5.34***	(1.67)	0.72	4.70***	(1.67)	0.62
RR	2.62	(1.89)	4.78***	(1.63)	0.64	3.36*	(1.72)	0.43	2.99*	(1.72)	0.38	2.61	(1.71)	0.33
NFA	2.80*	(1.61)	2.68**	(1.34)	0.44	2.78**	(1.35)	0.45	4.16***	(1.33)	0.66	3.20**	(1.37)	0.49
MOMS	3.04*	(1.56)	-0.75*	(0.39)	-0.56	1.77*	(1.04)	0.41	4.70***	(1.20)	0.90	5.53***	(1.28)	1.01
MOMM	2.84*	(1.63)	0.51	(0.68)	0.32	4.77***	(1.56)	0.68	2.68	(1.69)	0.36	3.06*	(1.68)	0.41
MOML	1.73	(1.82)	0.49	(0.64)	0.25	4.70***	(1.55)	0.67	1.67	(1.73)	0.22	1.97	(1.73)	0.26
VAL	3.52***	(1.67)	2.50**	(0.95)	0.65	0.40	(1.14)	0.08	3.67***	(1.31)	0.60	3.65**	(1.41)	0.59
VRP	0.98	(1.50)	3.29***	(1.05)	0.65	2.67**	(1.09)	0.51	0.30	(1.28)	0.05	-0.47	(1.28)	-0.08
VRPD	2.83*	(1.70)	4.62***	(1.54)	0.64	4.35***	(1.55)	0.60	3.41**	(1.62)	0.46	2.52	(1.64)	0.33
VRPU	2.69*	(1.55)	3.50***	(1.27)	0.63	3.91***	(1.26)	0.70	4.99***	(1.26)	0.88	5.07***	(1.26)	0.89
VRPUD	3.01*	(1.80)	4.91***	(1.68)	0.64	4.94***	(1.68)	0.64	4.68**	(1.77)	0.61	3.95**	(1.80)	0.50
			$\varphi(F_{1-6})$			$\varphi(F_{1-7})$			$\varphi(F_{1-8})$			$\varphi(F_{1-9})$		
μ_g	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g
SRP	5.64***	(1.65)	3.20**	(1.23)	0.57	4.05***	(1.32)	0.69	4.02***	(1.36)	0.69	3.78***	(1.36)	0.64
CAR	5.88***	(1.79)	4.22**	(1.59)	0.57	4.48***	(1.61)	0.60	5.02***	(1.65)	0.67	4.73***	(1.65)	0.63
RR	2.62	(1.89)	4.27**	(1.64)	0.56	3.18*	(1.70)	0.41	2.93*	(1.70)	0.37	2.76	(1.69)	0.35
NFA	2.80*	(1.61)	2.50*	(1.33)	0.41	2.70**	(1.35)	0.44	4.05***	(1.31)	0.63	3.54**	(1.35)	0.54
MOMS	3.04*	(1.56)	-0.82**	(0.36)	-0.53	1.48	(1.00)	0.35	3.76***	(1.16)	0.74	4.52***	(1.25)	0.80
MOMM	2.84*	(1.63)	0.19	(0.59)	0.14	4.23***	(1.56)	0.60	2.46	(1.67)	0.33	2.64	(1.65)	0.35
MOML	1.73	(1.82)	0.16	(0.57)	0.10	4.17***	(1.55)	0.59	1.70	(1.70)	0.22	1.81	(1.69)	0.23
VAL	3.52***	(1.67)	2.32**	(0.96)	0.57	0.51	(1.12)	0.10	3.27**	(1.29)	0.53	3.29**	(1.35)	0.53
VRP	0.98	(1.50)	2.93***	(1.06)	0.57	2.55**	(1.08)	0.49	0.78	(1.24)	0.14	0.11	(1.27)	0.02
VRPD	2.83*	(1.70)	4.09**	(1.53)	0.56	4.08**	(1.54)	0.56	3.48**	(1.58)	0.47	2.89*	(1.60)	0.38
VRPU	2.69*	(1.55)	3.03**	(1.24)	0.56	3.53***	(1.24)	0.77	4.51***	(1.24)	0.80	3.55**	(1.24)	0.80
VRPUD	3.01*	(1.80)	4.34**	(1.67)	0.56	4.61***	(1.67)	0.60	4.55**	(1.73)	0.59	4.17**	(1.76)	0.53
Panel B: Ex-SRP Sample (55 Test Assets)														
Model Free			$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$		
μ_g	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g
SRP	5.64***	(1.65)	3.20**	(1.23)	0.57	4.05***	(1.32)	0.69	4.02***	(1.36)	0.69	3.78***	(1.36)	0.64
CAR	5.88***	(1.79)	4.22**	(1.59)	0.57	4.48***	(1.61)	0.60	5.02***	(1.65)	0.67	4.73***	(1.65)	0.63
RR	2.62	(1.89)	4.27**	(1.64)	0.56	3.18*	(1.70)	0.41	2.93*	(1.70)	0.37	2.76	(1.69)	0.35
NFA	2.80*	(1.61)	2.50*	(1.33)	0.41	2.70**	(1.35)	0.44	4.05***	(1.31)	0.63	3.54**	(1.35)	0.54
MOMS	3.04*	(1.56)	-0.82**	(0.36)	-0.53	1.48	(1.00)	0.35	3.76***	(1.16)	0.74	4.52***	(1.25)	0.80
MOMM	2.84*	(1.63)	0.19	(0.59)	0.14	4.23***	(1.56)	0.60	2.46	(1.67)	0.33	2.64	(1.65)	0.35
MOML	1.73	(1.82)	0.16	(0.57)	0.10	4.17***	(1.55)	0.59	1.70	(1.70)	0.22	1.81	(1.69)	0.23
VAL	3.52***	(1.67)	2.32**	(0.96)	0.57	0.51	(1.12)	0.10	3.27**	(1.29)	0.53	3.29**	(1.35)	0.53
VRP	0.98	(1.50)	2.93***	(1.06)	0.57	2.55**	(1.08)	0.49	0.78	(1.24)	0.14	0.11	(1.27)	0.02
VRPD	2.83*	(1.70)	4.09**	(1.53)	0.56	4.08**	(1.54)	0.56	3.48**	(1.58)	0.47	2.89*	(1.60)	0.38
VRPU	2.69*	(1.55)	3.03**	(1.24)	0.56	3.53***	(1.24)	0.77	4.51***	(1.24)	0.80	3.55**	(1.24)	0.80
VRPUD	3.01*	(1.80)	4.34**	(1.67)	0.56	4.61***	(1.67)	0.60	4.55**	(1.73)	0.59	4.17**	(1.76)	0.53
			$\varphi(F_{1-6})$			$\varphi(F_{1-7})$			$\varphi(F_{1-8})$			$\varphi(F_{1-9})$		
μ_g	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g	SR	se	λ_g
SRP	5.64***	(1.65)	3.46**	(1.40)	0.58	3.46**	(1.40)	0.58	3.46**	(1.40)	0.58	3.46**	(1.40)	0.58
CAR	5.88***	(1.79)	4.77***	(1.66)	0.63	4.77***	(1.66)	0.63	4.77***	(1.66)	0.63	4.77***	(1.66)	0.63
RR	2.62	(1.89)	2.02	(1.76)	0.25	2.02	(1.76)	0.25	2.02	(1.76)	0.25	1.98	(1.78)	0.24
NFA	2.80*	(1.61)	3.02**	(1.45)	0.44	3.02**	(1.45)	0.44	3.02**	(1.45)	0.44	3.05**	(1.46)	0.44
MOMS	3.04*	(1.56)	3.47**	(1.40)	0.54	3.47**	(1.40)	0.54	3.47**	(1.40)	0.54	3.47**	(1.40)	0.54
MOMM	2.84*	(1.63)	2.97*	(1.67)	0.39	2.97*	(1.67)	0.39	2.97*	(1.67)	0.39	2.96*	(1.67)	0.39
MOML	1.73	(1.82)	2.58	(1.71)	0.33	2.58	(1.71)	0.33	2.58	(1.71)	0.33	2.56	(1.70)	0.32
VAL	3.52***	(1.67)	4.13**	(1.57)	0.57	4.13**	(1.57)	0.57	4.13**	(1.57)	0.57	4.13**	(1.58)	0.57
VRP	0.98	(1.50)	0.81	(1.37)	0.12	0.81	(1.37)	0.12	0.81	(1.37)	0.12	0.76	(1.37)	0.11
VRPD	2.83*	(1.70)	2.92*	(1.62)	0.38	2.92*	(1.62)	0.38	2.92*	(1.62)	0.38	2.89*	(1.62)	0.37
VRPU	2.69*	(1.55)	3.21**	(1.47)	0.49	3.21**	(1.47)	0.49	3.21**	(1.47)	0.49	3.30**	(1.47)	0.49
VRPUD	3.01*	(1.80)	3.47*	(1.77)	0.43	3.47*	(1.77)	0.43	3.47*	(1.77)	0.43	3.49*	(1.77)	0.44

Table A13: Latent-Factor Statistics and SDF Diagnostics: Sample Ex-SRP Portfolios

The table presents latent factor statistics and SDF diagnostics, obtained by implementing the first two steps of the RP-PCA three-pass estimator with optimal RP-weight (i.e., $\omega = 20$). We apply the estimator to the sample of $N = 55$ portfolios associated with the 11 currency investment strategies, thus excluding SRP portfolios from the test assets. We consider SDFs, $\varphi(F_{1-k})$, including an increasing number of latent factors, $k = 1, 2, \dots, 9$. 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, $\varphi_t = 1 - (\hat{F}_t - \mu_F) \hat{b}_{MV,k}^\top$. In *A.II: SDF Diagnostics*, we present the SDF diagnostics. Specifically, *II.a: 1P* shows the first-pass diagnostics: the average idiosyncratic variance, $\bar{\sigma}_\epsilon^2 = \frac{1}{N} \sum_{n=1}^N [Var(\hat{\epsilon}_n)/Var(X_n)]$; 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 $n = 1, \dots, N$ test assets, and $t = 1, \dots, T$ months. *II.b 2P* presents the second-pass diagnostics: the mean absolute errors (MAE) of the cross-sectional regression, $\bar{X}_n = \hat{\psi}_n \gamma^\top + a_n$, for $n = 1, \dots, N$, 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 $\hat{b}_{MV,k} = \mu_{F,k} / \sigma_{F,k}^2$, with $\mu_{F,k}$ and $\sigma_{F,k}^2$ denoting the k -th factor's mean and variance; ΔSR denotes the difference in SRs between SDFs with k and $k - 1$ factors. In Panel B, we apply the estimator to the $N = 55$ portfolios, which exclude SRP portfolios from the baseline cross section. We present the same factor statistics and SDF diagnostics used to assess the baseline evidence.

	A.I: Factor Statistics				A.II: SDF Diagnostics					
	I.a: Factors				II.a: 1P		II.b: 2P		II.c: mSR	
	$\mu_{F,k}$	$SR_{F,k}$	$\hat{b}_{F,k}$		$\bar{\sigma}_\epsilon^2$	$\overline{RMS}_\alpha$	MAE	$R^2(\%)$	SR	ΔSR
F_1	12.17	0.23	0.04	$\varphi(F_1)$	21.11	1.07	0.82	66.37	0.23	.
F_2	6.43**	0.52	0.35	$\varphi(F_{1-2})$	16.33	0.90	0.47	77.89	0.57	0.34
F_3	5.19***	0.58	0.54	$\varphi(F_{1-3})$	13.85	0.77	0.30	91.53	0.81	0.24
F_4	4.99***	0.81	1.09	$\varphi(F_{1-4})$	12.67	0.59	0.14	98.09	1.15	0.33
F_5	1.96	0.32	0.42	$\varphi(F_{1-5})$	11.55	0.55	0.13	98.32	1.19	0.04
F_6	1.75	0.31	0.45	$\varphi(F_{1-6})$	10.61	0.52	0.12	98.63	1.23	0.04
F_7	2.43**	0.49	0.81	$\varphi(F_{1-7})$	9.88	0.45	0.09	99.17	1.32	0.09
F_8	0.29	0.06	0.11	$\varphi(F_{1-8})$	9.24	0.45	0.09	99.18	1.32	0.00
F_9	0.22	0.05	0.09	$\varphi(F_{1-9})$	8.64	0.45	0.09	99.18	1.32	0.00

Table A14: Risk Exposures of Tradable Factors: Sample Ex-SRP Portfolios

The table presents the 12 tradable, HML factors' exposures to the latent factors (A.I: Risk Exposure, η_{F_k}) and the explained variations (A.II: Explained Variation, $R^2_{F_{1-k}}$) obtained from the spanning regressions including an increasing number of factors, $k = 1, \dots, K$. We report the exposures to the first six extracted, orthogonalized latent factors (i.e., $K = 6$). Latent factors are extracted by applying rpPCA (with RP-weight $\omega = 20$) to the sample which considers the portfolios obtained from the 11 investment strategies ($N = 55$), thus excluding SRP portfolios. Based on Newey-West standard errors, ***, **, * denote statistical significance at the 1-, 5- and 10-percent levels, respectively.

	A.I: Risk Exposures						A.II: Explained Variation					
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$
SRP	0.06***	0.39***	0.16***	-0.01	-0.12**	-0.06	17.64	64.75	69.01	68.90	69.92	70.08
CAR	0.06***	0.55***	0.05**	0.11**	-0.15***	-0.06	14.02	82.61	82.86	83.48	84.77	84.87
RR	0.08***	0.52***	-0.21***	-0.05	-0.08**	-0.18***	21.76	77.61	82.39	82.46	82.77	84.21
NFA	0.11***	0.18***	0.04	0.27***	-0.26**	-0.29***	56.96	65.56	65.66	70.44	74.99	79.71
MOMS	-0.02	-0.09*	0.44***	0.46***	0.38***	0.19***	1.71	3.49	31.16	45.23	55.41	57.48
MOMM	-0.02	0.07	0.78***	-0.35***	0.09	-0.12**	1.20	1.82	70.22	76.92	77.28	77.85
MOML	-0.03*	0.08	0.77***	-0.49***	0.05	0.12***	2.33	3.18	68.80	81.63	81.72	82.36
VAL	0.04***	0.29***	-0.35***	0.55***	0.01	0.43***	5.38	25.75	41.05	59.45	59.31	68.70
VRP	0.05***	0.36***	-0.07*	-0.36***	-0.34***	0.49***	13.24	50.39	51.03	60.08	68.57	83.38
VRPD	0.08***	0.48***	-0.00	-0.12*	-0.30***	0.22***	26.84	81.11	81.04	81.82	87.11	89.50
VRPU	0.06***	0.35***	0.10**	0.16***	0.09*	-0.55***	19.07	53.67	54.87	56.47	56.95	74.72
VRPUD	0.08***	0.52***	0.05*	-0.01	-0.19***	-0.04	26.47	84.06	84.33	84.28	86.23	86.26

Table A15: Risk Premia of Tradable Factors: Sample Ex-SRP Portfolios

The table presents the rpPCA three-pass risk-premium estimates for the HML tradable factors associated with the 12 currency investment strategies. We implement rpPCA with baseline RP-weight $\omega = 20$, using models of different dimension, denoted by SDFs with increasing number of factors, i.e., $\varphi(F_{1-k})$ with $k = 2, \dots, 6$. 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 de-noised counterpart to the original candidate factor. ***, **, * denote significance, respectively, at the 1-, 5- and 10-percent levels. Latent factors are extracted by applying rpPCA (with RP-weight $\omega = 20$) to the sample of $N = 55$ portfolios, which exclude the SRP portfolios from the baseline sample.

	Model Free			$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$			$\varphi(F_{1-6})$		
	μ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR
SRP	5.64***	(1.65)	0.80	3.20**	(1.23)	0.57	4.05***	(1.32)	0.69	4.02***	(1.36)	0.69	3.78***	(1.36)	0.64	3.67**	(1.40)	0.62
CAR	5.88***	(1.79)	0.72	4.22**	(1.59)	0.57	4.48***	(1.61)	0.60	5.02***	(1.65)	0.67	4.73***	(1.65)	0.63	4.63***	(1.66)	0.62
RR	2.62	(1.89)	0.31	4.27**	(1.64)	0.56	3.18*	(1.70)	0.41	2.93*	(1.70)	0.37	2.76	(1.69)	0.35	2.44	(1.74)	0.31
NFA	2.80*	(1.61)	0.37	2.50*	(1.33)	0.41	2.70**	(1.35)	0.44	4.05***	(1.31)	0.63	3.54**	(1.35)	0.54	3.03**	(1.43)	0.45
MOMS	3.04*	(1.56)	0.40	-0.82**	(0.36)	-0.53	1.48	(1.00)	0.35	3.76***	(1.16)	0.74	4.52***	(1.25)	0.80	4.86***	(1.29)	0.85
MOMM	2.84*	(1.63)	0.34	0.19	(0.59)	0.14	4.23***	(1.56)	0.60	2.46	(1.67)	0.33	2.64	(1.65)	0.35	2.43	(1.67)	0.33
MOML	1.73	(1.82)	0.20	0.16	(0.57)	0.10	4.17***	(1.55)	0.59	1.70	(1.70)	0.22	1.81	(1.69)	0.23	2.03	(1.68)	0.26
VAL	3.52**	(1.67)	0.44	2.32**	(0.96)	0.57	0.51	(1.12)	0.10	3.27**	(1.29)	0.53	3.29**	(1.35)	0.53	4.04***	(1.41)	0.61
VRP	0.98	(1.50)	0.13	2.93***	(1.06)	0.57	2.55**	(1.08)	0.49	0.78	(1.24)	0.14	0.11	(1.27)	0.02	0.96	(1.35)	0.14
VRPD	2.83*	(1.70)	0.35	4.09**	(1.53)	0.56	4.08**	(1.54)	0.56	3.48**	(1.58)	0.47	2.89*	(1.60)	0.38	3.28**	(1.61)	0.43
VRPU	2.69*	(1.55)	0.36	3.03**	(1.24)	0.56	3.53***	(1.24)	0.64	4.33***	(1.24)	0.77	4.51***	(1.24)	0.80	3.55**	(1.42)	0.55
VRPUD	3.01*	(1.80)	0.36	4.34**	(1.67)	0.56	4.61***	(1.67)	0.60	4.55**	(1.73)	0.59	4.17**	(1.76)	0.53	4.10**	(1.76)	0.52

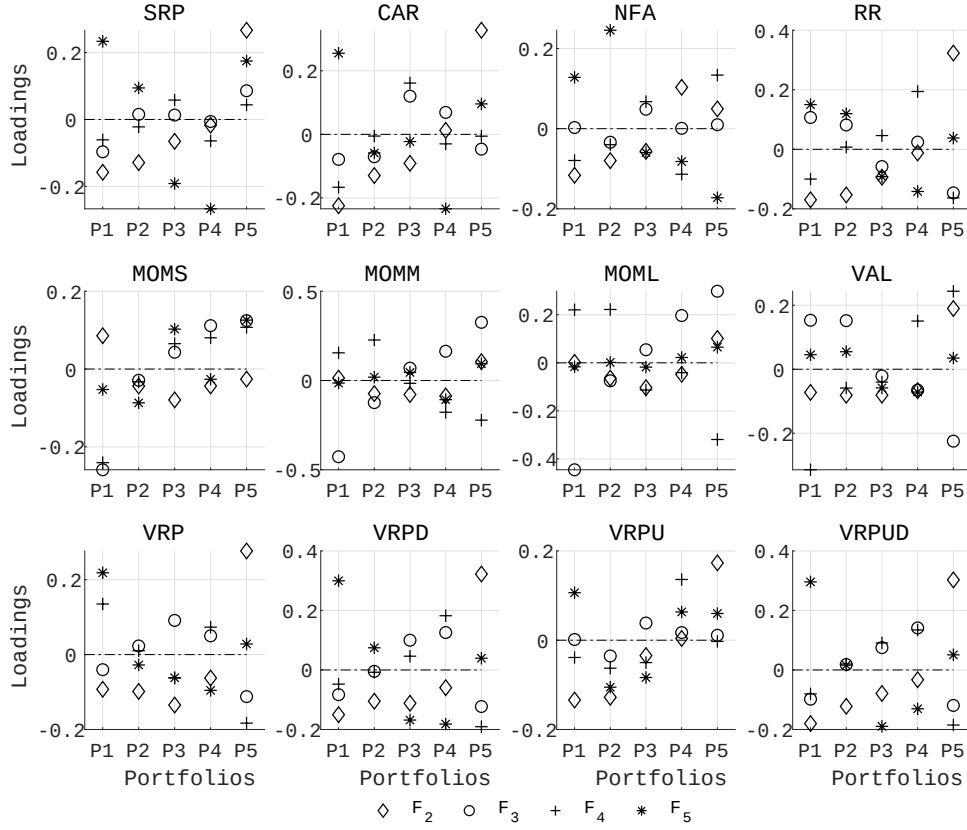
Table A16: Tradable and Nontradable SRP Factor Risk Premia by Cross-Sections

The table presents the three-pass risk-premium estimates for the SRP tradable (Panel A) and nontradable (Panel B) factors for cross sections consisting of 50 test assets. In addition to the five SRP portfolios, we exclude the portfolios of the selected strategy. We implement rpPCA with baseline RP-weight $\omega = 20$, using models of different dimension, denoted by SDF with increasing number of factors, i.e., $\varphi(F_{1-k})$ with $k = 2, \dots, 9$. For each model, we report the risk-premium estimates (λ_g); the asymptotic standard errors (se); and the annualized Sharpe ratios (SR) associated with the projected factor, i.e., the de-noised counterpart to the original candidate factor. ***, **, * denote significance, respectively, at the 1-, 5- and 10-percent levels.

Panel A: Tradable SRP Factor																								
Model Free	$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$			$\varphi(F_{1-6})$			$\varphi(F_{1-7})$			$\varphi(F_{1-8})$			$\varphi(F_{1-9})$		
	μ_g	se	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	
CAR	5.64***	(1.65)	2.62**	(1.18)	0.47	3.49***	(1.29)	0.61	3.42**	(1.35)	0.59	3.36**	(1.34)	0.58	3.24**	(1.37)	0.56	3.02**	(1.38)	0.52	3.01**	(1.38)	0.52	
NFA	5.64***	(1.65)	3.21**	(1.22)	0.57	4.06***	(1.32)	0.70	4.07***	(1.35)	0.70	3.97***	(1.35)	0.68	3.81***	(1.39)	0.64	3.53**	(1.40)	0.59	3.55**	(1.41)	0.60	
RR	5.64***	(1.65)	3.61***	(1.25)	0.63	4.08***	(1.31)	0.70	3.89***	(1.35)	0.67	3.76***	(1.36)	0.64	3.69**	(1.38)	0.62	3.38**	(1.40)	0.57	3.38**	(1.40)	0.57	
MOMS	5.64***	(1.65)	3.09**	(1.22)	0.55	3.73***	(1.31)	0.64	3.86***	(1.32)	0.66	3.53**	(1.33)	0.60	3.21**	(1.38)	0.54	3.23**	(1.37)	0.55	3.23**	(1.38)	0.55	
MOMM	5.64***	(1.65)	2.98**	(1.21)	0.53	4.29***	(1.34)	0.74	3.99***	(1.35)	0.68	3.80***	(1.36)	0.64	3.57**	(1.40)	0.60	3.40**	(1.39)	0.57	3.42**	(1.39)	0.57	
MOML	5.64***	(1.65)	3.06**	(1.21)	0.55	4.34***	(1.33)	0.75	3.87***	(1.38)	0.66	3.74***	(1.38)	0.63	3.69**	(1.40)	0.62	3.58**	(1.40)	0.60	3.57**	(1.40)	0.60	
VAL	5.64***	(1.65)	3.19**	(1.27)	0.55	3.82***	(1.34)	0.65	4.00***	(1.36)	0.68	3.82***	(1.36)	0.64	3.77***	(1.39)	0.64	3.57**	(1.39)	0.60	3.65**	(1.38)	0.61	
VRP	5.64***	(1.65)	3.52***	(1.25)	0.61	4.12***	(1.32)	0.70	4.05***	(1.35)	0.69	3.70**	(1.39)	0.63	3.47**	(1.38)	0.58	3.48**	(1.39)	0.58	3.49**	(1.39)	0.59	
VRPD	5.64***	(1.65)	3.52***	(1.24)	0.62	4.11***	(1.31)	0.71	3.88***	(1.36)	0.67	3.64**	(1.39)	0.62	3.69**	(1.39)	0.63	3.40**	(1.40)	0.58	3.38**	(1.41)	0.57	
VRPU	5.64***	(1.65)	2.96**	(1.22)	0.53	3.90***	(1.32)	0.67	4.03***	(1.35)	0.69	3.76***	(1.37)	0.65	3.77***	(1.35)	0.65	3.58**	(1.38)	0.61	3.58**	(1.38)	0.61	
VRPUD	5.64***	(1.65)	3.46***	(1.24)	0.61	4.20***	(1.31)	0.72	4.04***	(1.36)	0.69	4.05***	(1.36)	0.69	3.85***	(1.39)	0.65	3.61**	(1.39)	0.61	3.60**	(1.39)	0.61	

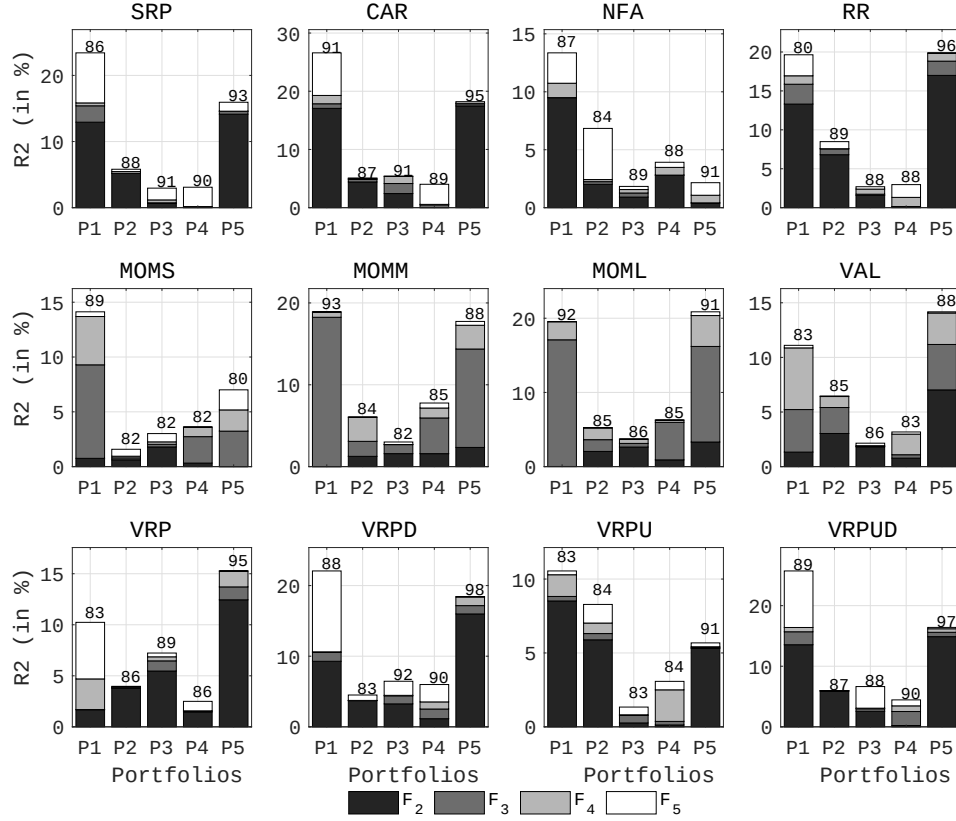
Panel B: Nontradable SRP Factor																								
Model Free	$\varphi(F_{1-2})$			$\varphi(F_{1-3})$			$\varphi(F_{1-4})$			$\varphi(F_{1-5})$			$\varphi(F_{1-6})$			$\varphi(F_{1-7})$			$\varphi(F_{1-8})$			$\varphi(F_{1-9})$		
	μ_g	se	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	λ_g	se	SR	
CAR	-	-	0.71**	(0.33)	0.47	0.93**	(0.37)	0.60	1.08**	(0.42)	0.69	1.02**	(0.42)	0.59	0.97**	(0.42)	0.56	1.07**	(0.40)	0.61	1.06**	(0.40)	0.60	
NFA	-	-	0.88**	(0.35)	0.57	1.10***	(0.39)	0.70	1.31***	(0.43)	0.82	1.21***	(0.43)	0.68	1.16**	(0.43)	0.65	1.20***	(0.41)	0.67	1.21***	(0.41)	0.67	
RR	-	-	1.00***	(0.36)	0.64	1.12***	(0.39)	0.70	1.19***	(0.43)	0.74	1.07**	(0.44)	0.62	1.05**	(0.44)	0.61	1.18***	(0.41)	0.67	1.19***	(0.41)	0.67	
MOMS	-	-	0.85**	(0.35)	0.55	1.04***	(0.38)	0.65	1.41***	(0.40)	0.84	1.17***	(0.42)	0.67	1.19***	(0.42)	0.68	1.19***	(0.40)	0.68	1.20**	(0.40)	0.67	
MOMM	-	-	0.81**	(0.34)	0.53	1.21***	(0.41)	0.76	1.23***	(0.43)	0.77	1.02**	(0.44)	0.59	1.01**	(0.44)	0.58	1.06**	(0.40)	0.60	1.05**	(0.40)	0.60	
MOML	-	-	0.84**	(0.35)	0.55	1.22***	(0.42)	0.76	1.18***	(0.43)	0.74	1.03**	(0.44)	0.59	1.03**	(0.44)	0.59	1.13***	(0.41)	0.64	1.13***	(0.41)	0.64	
VAL	-	-	0.87***	(0.36)	0.56	1.20***	(0.40)	0.65	1.20***	(0.44)	0.75	1.01**	(0.45)	0.58	1.05**	(0.45)	0.60	1.18***	(0.41)	0.67	1.26***	(0.40)	0.70	
VRP	-	-	0.97***	(0.36)	0.62	1.12***	(0.39)	0.70	1.36***	(0.42)	0.84	1.08**	(0.43)	0.63	1.18***	(0.43)	0.68	1.21***	(0.40)	0.69	1.21***	(0.40)	0.68	
VRPD	-	-	0.97***	(0.36)	0.63	1.10***	(0.39)	0.70	1.15**	(0.44)	0.73	1.00**	(0.45)	0.61	1.06**	(0.44)	0.62	1.25***	(0.41)	0.72	1.25***	(0.41)	0.71	
VRPU	-	-	0.83**	(0.35)	0.53	1.10***	(0.39)	0.68	1.43***	(0.42)	0.86	1.17***	(0.44)	0.67	1.24***	(0.44)	0.70	1.27***	(0.41)	0.72	1.24***	(0.41)	0.70	
VRPUD	-	-	0.97***	(0.36)	0.62	1.14***	(0.40)	0.71	1.20***	(0.44)	0.75	1.22***	(0.44)	0.71	1.11**	(0.45)	0.63	1.23***	(0.42)	0.69	1.22***	(0.43)	0.69	

Figure A2: Portfolio Risk Exposures to Latent Factors



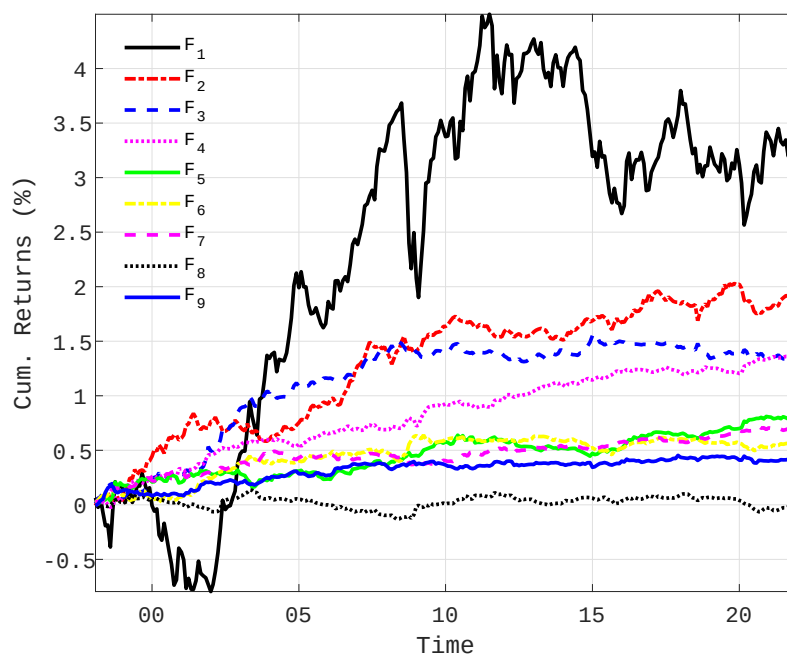
The figure shows portfolio loadings on the second, third, fourth, and fifth estimated latent factors from the panel of currency portfolios excess returns by means of RP-PCA with baseline RP-weight, i.e., $\omega = 20$. We omit to report exposures to the first factor, to better visualize the evidence 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, $\tilde{X}_{n,t} = \tilde{F}_t \tilde{\psi}_n^\top + \tilde{e}_{n,t}$, $n = 1, \dots, N$, $t = 1, \dots, T$. 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^2 s obtained by regressing currency portfolios' excess returns (X_{nt}) on the first five estimated orthogonalized latent factors ($\hat{F}_t = [\hat{F}_{1t}, \dots, \hat{F}_{kt}]$, with $k = 6$). 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, $X_{nt} = \alpha_n + \hat{F}_{1:kt} \psi_n^\top + e_{nt}$, $n = 1, \dots, N$, $t = 1, \dots, T$, $k = 1, \dots, K$, with $\hat{F}_{1:kt} = [\hat{F}_{1t}, \dots, \hat{F}_{kt}]$. 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^2 s 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 ($T = 287$).

Table A17: Investment Strategy Combos with SRP

The table presents the pairwise equally-weighted combinations of each investment strategy with SRP. Panel A.I presents the sample average return (Avg.), skewness (skew), and Sharper ratio (sr) of the noisy 12 tradable HML factors' (Fct), and of the noisy factor combinations between each of the 12 HML factor and SRP (combo). Panel A.II reports the combination of each de-noised factor with the de-noised SRP with SDFs (F_{1-k}) including an increasing number of factors, $k = 1, \dots, 9$. Factors are de-noised using the rpPCA three-pass estimator with RP-weight $\omega = 20$. The cross-section of test assets consists of the $N = 60$ portfolios obtained from the 12 investment strategies. The SRP panel simply reports the statistics of the noisy SRP factor and of de-noised SRP, for easy of comparison Based on Newey-West standard errors, ***, **, * denote statistical significance at the 1-, 5- and 10-percent levels, respectively.

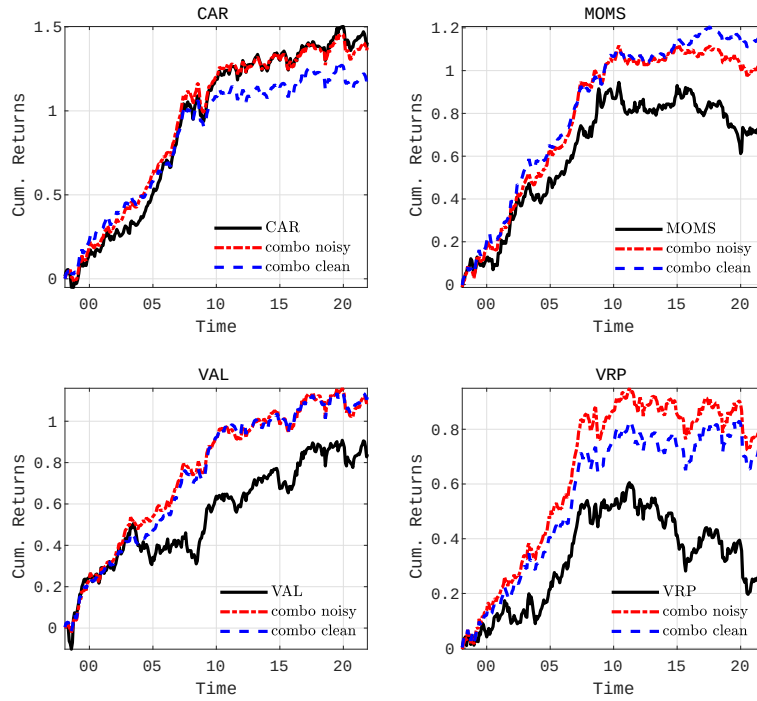
	A.I: Noisy Factors		A.II: De-Noised Factors (Combo)								
	Fct.	Combo	F_1	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}
SRP											
avg	5.64***	5.64***	0.70	3.88***	4.78***	5.07***	4.79***	4.73***	4.84***	4.86***	5.44***
skew	-0.64	-0.64	-0.37	-0.62	-0.48	-0.43	-0.47	-0.48	-0.49	-0.50	-0.52
sr	0.80	0.80	0.23	0.65	0.78	0.82	0.77	0.76	0.78	0.78	0.85
CAR											
avg	5.88***	5.76***	0.71	4.36***	4.82***	5.21***	4.74***	4.66***	4.75***	4.75***	4.98***
skew	-0.47	-0.63	-0.37	-0.58	-0.52	-0.46	-0.51	-0.52	-0.52	-0.52	-0.52
sr	0.72	0.81	0.23	0.65	0.72	0.77	0.70	0.69	0.70	0.70	0.73
RR											
avg	2.62	4.13**	0.82	4.33***	4.07***	4.03***	3.70**	3.45**	3.25**	3.25**	3.63**
skew	-0.51	-0.61	-0.37	-0.65	-0.67	-0.67	-0.73	-0.74	-0.71	-0.71	-0.67
sr	0.31	0.58	0.23	0.65	0.60	0.60	0.55	0.51	0.48	0.48	0.53
NFA											
avg	2.80*	4.22***	1.02	3.28***	3.78***	4.61***	3.99***	3.68***	3.79***	3.78***	4.16***
skew	-0.93	-0.93	-0.37	-0.83	-0.80	-0.63	-0.69	-0.76	-0.78	-0.81	-0.77
sr	0.37	0.66	0.23	0.57	0.66	0.79	0.67	0.61	0.63	0.63	0.68
MOMS											
avg	3.04*	4.34***	0.22	1.56***	3.28***	4.88***	5.16***	5.28***	4.38***	4.40***	4.85***
skew	0.52	0.28	-0.37	-0.52	0.16	0.33	0.28	0.30	0.21	0.34	0.19
sr	0.40	0.86	0.23	0.66	0.90	1.22	1.28	1.30	1.02	1.01	1.08
MOMM											
avg	2.84*	4.24***	0.23	2.19***	4.78***	3.87***	3.93***	3.77***	4.16***	4.17***	4.20***
skew	0.01	-0.02	-0.37	-0.41	0.22	0.04	0.05	0.03	-0.03	0.01	0.00
sr	0.34	0.72	0.23	0.66	0.90	0.72	0.73	0.69	0.76	0.76	0.76
MOML											
avg	1.73	3.69***	0.19	2.18***	4.74***	3.37***	3.38***	3.49***	3.72***	3.71***	3.81***
skew	-0.10	0.02	-0.37	-0.36	0.23	-0.07	-0.07	-0.06	-0.10	-0.11	-0.12
sr	0.20	0.62	0.23	0.65	0.89	0.62	0.62	0.63	0.68	0.67	0.69
VAL											
avg	3.52**	4.58***	0.57	3.19***	2.59**	4.37***	4.22***	4.68***	4.79***	4.82***	4.67***
skew	-0.07	-0.54	-0.37	-0.62	-0.68	-0.26	-0.28	-0.27	-0.28	-0.35	-0.32
sr	0.44	0.76	0.23	0.65	0.52	0.82	0.79	0.85	0.88	0.86	0.83
VRP											
avg	0.98	3.31**	0.66	3.59***	3.73***	2.69**	2.16*	2.70**	2.70**	2.72**	2.97**
skew	-0.65	-0.83	-0.37	-0.63	-0.62	-0.82	-0.94	-0.91	-0.91	-0.94	-0.91
sr	0.13	0.53	0.23	0.65	0.67	0.48	0.38	0.46	0.46	0.46	0.50
VRPD											
avg	2.83*	4.23***	0.84	4.25***	4.57***	4.24***	3.65**	3.88***	3.76**	3.77**	4.12***
skew	-0.77	-0.76	-0.37	-0.67	-0.64	-0.69	-0.78	-0.77	-0.75	-0.76	-0.74
sr	0.35	0.60	0.23	0.64	0.69	0.64	0.54	0.57	0.55	0.56	0.60
VRPU											
avg	2.69*	4.17***	0.73	3.69***	4.35***	5.03***	4.93***	4.29***	4.24***	4.25***	4.92***
skew	-0.37	-0.52	-0.37	-0.67	-0.57	-0.45	-0.46	-0.54	-0.53	-0.53	-0.51
sr	0.36	0.63	0.23	0.64	0.74	0.85	0.84	0.70	0.69	0.69	0.78
VRPUD											
avg	3.01*	4.33***	0.86	4.40***	4.86***	4.87***	4.37***	4.29***	3.99**	3.99**	4.50***
skew	-0.63	-0.67	-0.37	-0.66	-0.61	-0.61	-0.68	-0.68	-0.64	-0.65	-0.62
sr	0.36	0.59	0.23	0.64	0.71	0.71	0.63	0.62	0.57	0.57	0.64

Table A18: 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 ($R_{F_{1-k}}^2$); 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.

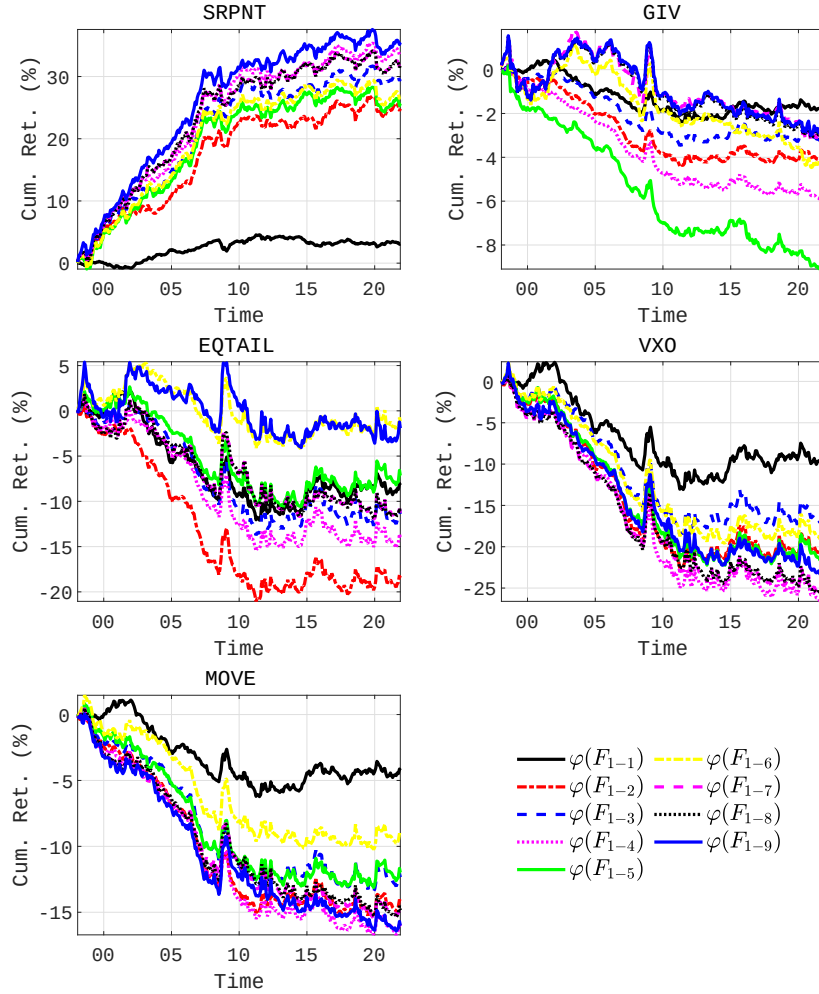
Panel A: SRP Factor									
k	1	2	3	4	5	6	7	8	9
SRP _{NT}									
η_{F_k}	0.01***	0.12***	0.04*	0.03	-0.10***	0.02	0.07**	-0.01	0.08*
$R_{F_{1-k}}^2$	2.24	20.22	20.79	20.77	24.28	24.12	24.97	24.71	25.56
$\lambda_{F_{1-k}}$	0.13	1.04***	1.24***	1.41***	1.07**	1.12**	1.33***	1.33***	1.48***
$sr_{F_{1-k}}$	0.23	0.66	0.77	0.87	0.61	0.64	0.74	0.74	0.81
Panel B: Other Nontradable Factors									
k	1	2	3	4	5	6	7	8	9
EQTAIL									
η_{F_k}	-0.03***	-0.05**	0.05**	-0.02	0.09*	0.11	-0.14***	0.01	0.20***
$R_{F_{1-k}}^2$	17.76	21.51	23.11	22.95	25.44	28.54	32.64	32.42	39.60
$\lambda_{F_{1-k}}$	-0.34	-0.77**	-0.48	-0.59	-0.30	-0.05	-0.47	-0.47	-0.08
$sr_{F_{1-k}}$	0.23	0.47	0.28	0.35	0.17	0.03	0.23	0.23	0.04
GIV									
η_{F_k}	-0.01	-0.01	0.01	-0.02	-0.04	0.09	0.02	-0.04	0.00
$R_{F_{1-k}}^2$	0.37	0.22	-0.10	-0.34	-0.12	1.54	1.25	1.29	0.93
$\lambda_{F_{1-k}}$	-0.07	-0.16	-0.13	-0.24	-0.37	-0.18	-0.13	-0.13	-0.13
$sr_{F_{1-k}}$	0.23	0.49	0.37	0.67	0.84	0.27	0.19	0.19	0.18
VXO									
η_{F_k}	-0.03***	-0.06***	0.03	-0.07**	0.06	0.05	-0.09***	0.05	0.06
$R_{F_{1-k}}^2$	20.89	25.17	25.46	26.65	27.82	28.13	29.85	30.07	30.44
$\lambda_{F_{1-k}}$	-0.37	-0.83**	-0.66*	-1.07**	-0.86	-0.76	-1.04**	-1.04**	-0.92*
$sr_{F_{1-k}}$	0.23	0.47	0.37	0.59	0.46	0.40	0.54	0.53	0.47
MOVE									
η_{F_k}	-0.01***	-0.05**	0.01	-0.03	0.05	0.05*	-0.08**	0.04	-0.03
$R_{F_{1-k}}^2$	4.46	8.03	7.85	7.74	8.38	8.75	9.81	9.90	9.69
$\lambda_{F_{1-k}}$	-0.18	-0.60**	-0.52	-0.67**	-0.50	-0.39	-0.63*	-0.62*	-0.67
$sr_{F_{1-k}}$	0.23	0.58	0.50	0.64	0.46	0.34	0.52	0.51	0.54

Figure A5: Selected Strategy Combos



The figure shows the cumulative returns of selected factors, and their pairwise combinations (combo) with SRP. We present two types of combos. The first simply averages over the noisy factors. The second averages over the de-noised versions of the factors. Factors are de-noised using the SDF consisting of the first six latent factors, extracted via the RP-PCA three-pass estimator with RP-weight $\omega = 20$.

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 $K = 9$ de-noised versions by expanding the dimension of the SDF, i.e., $\varphi(F_{1-k})$ with $k = 1, 2, \dots, K$. 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 ($T = 287$).