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CURRENCY RISK PREMIUMS REDUX

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Abstract

We study a large currency cross section using asset pricing methods which account for omitted-variable and measurement-error biases. First, we show that the pricing kernel includes at least three latent factors which resemble (but are not identical to) a strong U.S. "Dollar" factor, and two weak, high Sharpe ratio "Carry" and "Momentum" slope factors. Evidence for an additional "Value" factor is weaker. Second, using this pricing kernel, we find that only a small fraction of the over 100 nontradable candidate factors considered have a statistically significant risk premium – mostly relating to volatility, uncertainty and liquidity conditions, rather than macro variables.

JEL Classification: F31, G12, G15.
Keywords: currency risk premiums, asset pricing, omitted factors, measurement error, weak factors.
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1 Introduction[1]

In the foreign exchange (FX) market, the price of risk represents the compensation required by investors for a unit exposure to the systematic risk resulting from holding investments denominated in foreign currencies. Since the seminal paper of Lustig and Verdelhan (2007), cross-sectional asset pricing has been applied successfully to currency returns, and a growing literature continues to develop with the aim of explaining the cross section of currency returns and to provide estimates of the price of currency risk. At the same time, we have also observed a proliferation of currency investment strategies, which attract a large fraction of the over 6 trillion U.S. dollars traded in currency markets daily. It is therefore crucial, for investors and market observers alike, to uncover the sources of the underlying risk-return trade-off in this titanic market. To this end, in this paper we provide new evidence on the optimal factor model for currency returns and robust estimates of currency risk premiums.[2]

Thus far, the FX literature has largely established the risk-return trade-off in terms of *tradable* risk factors. These factors represent convolutions of returns associated with currency investment strategies (e.g., carry and momentum factors) and therefore prevent a deep economic interpretation. Only a few papers focus on *nontradable* risk factors, i.e., factors representing macroeconomic and financial risks such as for example the global volatility factor of Menkhoff et al. (2012a). But this strand of the literature is evolving rapidly, so that we observe also a proliferation of FX risk factors, i.e., a "factor zoo", albeit much more contained than for equities (e.g., Feng et al., 2020).[3]

When a new candidate factor is proposed, the first goal is to determine its risk premium (or price of risk). If the factor is tradable, a model-free estimate of its risk premium is readily available, being simply the time-series average of its excess return (Cochrane, 2005).

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[2]The most popular currency strategies include carry-trade strategies based on interest rate differentials across countries (e.g., Lustig et al., 2011; Menkhoff et al., 2012a; Lettau et al., 2014), momentum strategies based on past currency returns (e.g., Menkhoff et al., 2012b, Asness et al., 2013), value strategies based on deviations from purchasing power parity (e.g., Asness et al., 2013; Kroencke et al., 2014; Menkhoff et al., 2017), global imbalances strategies based on imbalances in trade and capital flows (Della Corte et al., 2016b), and macro strategies based on, for example, output gap differentials (Colacito et al., 2020).

[3]At first, the empirical asset pricing literature rested on a single factor, namely the market factor, to price the cross section of stock returns (Sharpe, 1964; Lintner, 1965). Since then, more than 300 risk factors have been claimed to explain stock returns with some statistical significance (Harvey et al., 2016), but some of these factors could just be "lucky" (Harvey and Liu, 2021).

By contrast, if the factor is nontradable, the task of estimating its risk premium is not trivial. A nontradable factor is by definition a non-return-based factor and, as a consequence, its mean is not informative about its price of risk. Therefore, one needs to recur to statistical methods, such as for example the standard two-pass procedure of Fama and MacBeth (1973) – FMB hereafter – to obtain an estimate of the factor risk premium.

While the two-pass FMB procedure can be easily implemented, the resulting price of risk estimates can be biased for two main reasons. First, some relevant factors entering the pricing kernel, or stochastic discount factor (SDF), could be omitted (omitted-variable bias). Second, the candidate factor could be measured with noise (measurement-error bias). Recently, Giglio and Xiu (2021) developed a three-pass procedure that helps address both sources of bias by exploiting the information contained in a reasonably large cross section of test assets. This literature, albeit very young, has already established a set of useful results for the U.S. stock market. In this paper, we build on this literature but shift the focus to currency markets. Specifically, we address the following two questions: How many (and which) factors should the optimal currency SDF comprise? Which nontradable factors, out of the plethora of factors proposed in the finance literature, have statistically significant currency risk premiums?

The FX literature has generally looked at each investment strategy in isolation, therefore resting on small cross sections of test assets. However, the use of a limited cross section of test assets may not provide a robust test of an asset pricing model (Lewellen et al., 2010). In addition, the omitted-variable and measurement-error problems inherent in the estimation of the prices of risk have not been taken fully into account. For these reasons, it is fair to argue that the economic sources of the risk-return trade-off underlying popular currency investment strategies are still hotly debated. To fill this gap, we estimate the risk premiums of a long list of nontradable macro-financial candidate factors from a reasonably large cross section of currency portfolios, or test assets. We do this by combining the three-pass model of Giglio and Xiu (2021) with the statistical method of Lettau and Pelger (2020a,b).

The three-pass method of Giglio and Xiu (2021) – GX hereafter – that we employ to revisit the macro-financial determinants of currency risk premiums serves our purpose, as it tackles both the omitted-variable and measurement-error problems. To do so, it exploits the information contained in the panel of test-asset returns and, in particular, in the underlying latent pricing factors that are extracted from the panel of returns. In practice, this procedure projects the nontradable candidate factors onto the space spanned by the latent pricing factors. The nontradable factors' risk-premium estimates are then simply given by linear combinations of the prices of risk of the latent pricing factors. In this way, one can remain agnostic about the set of 'true' risk factors, and yet obtain robust estimates of nontradable factors' risk premiums.

It is evident, however, that the method of GX heavily relies first on estimating the latent factors, and then on determining the factor structure of the optimal SDF, i.e., the relevant pricing factors. For this reason, we amend the GX procedure by resorting to the Risk-Premium Principal Component Analysis (RP-PCA) method of Lettau and Pelger (2020a,b) – LP hereafter. In essence, RP-PCA is a generalized version of PCA, regularized by a pricing-error penalty term (named risk-premium weight or RP-weight), which "overweights" the test-asset mean returns relative to their variances. As a result, the estimated factors fit not only the time series, but also the cross section of expected returns. Strong systematic factors should be estimated more efficiently, and weak factors which possess high risk premiums (Sharpe ratios) can be detected more easily. We refer to this combined procedure that uses the methods developed separately by GX and LP as the augmented three-pass method, and we show that the use of RP-PCA enhances the three-pass model pricing performance.

In the empirical analysis, the underlying FX data consist of 49 individual currencies sampled at monthly frequency, from 1983 to 2017. We take the perspective of a U.S. investor, so that the individual currencies are expressed relative to the U.S. dollar. In the baseline analysis, the test assets consist of 46 currency portfolios, resulting from nine of the most popular currency investment strategies. Turning to the nontradable candidate risk factors, our list consists of more than 100 factors, which we categorize into three groups: financial, macro, and text-based factors. The latter factors are obtained by aggregating into an index news coverage about specific sources of uncertainty. To our knowledge, we are the first to consider such a large number of nontradable factors, capturing a wide range of macro-financial risks, and assess their implications for currency returns. Based on this extensive dataset, we uncover a number of interesting findings that help shed light (i) on the optimal latent-factor currency SDF, and (ii) on the macro-financial sources of the risk-return trade-off inherent in currency investment strategies. We present the findings in this order.

First, we show that the currency SDF consists of at least three latent pricing factors. The first factor is a strong factor, while the remaining two explain fewer portfolios, and hence are in line with a weak-factor interpretation. Yet, these weak factors are relevant pricing factors, as they display high Sharpe ratios, and hence cannot be excluded from the SDF. Notably, the third factor is detected by RP-PCA but not by standard PCA. Hence, by neglecting the information in the portfolio mean returns, one incurs the risk of omitting relevant factors with high Sharpe ratios, which can in turn distort the nontradable factors' risk-premium estimates. This is because RP-PCA changes materially the information spanned by the factors relative to PCA in a way that the estimated factors should be closer to the underlying 'true' pricing factors. Importantly, we also document that, while the pricing accuracy improves with the RP-weights, the explained systematic variance remains essentially unchanged. Thus, in practice, there is no trade-off in choosing even very high RP-weights.[4]

Moreover, the analysis of the portfolio risk exposures reveals that the extracted, orthogonalized latent factors retain a clear economic interpretation. The first latent factor resembles the Dollar factor (e.g., Lustig et al., 2011; Verdelhan, 2018), as it primarily plays the role of a currency level factor with similar positive factor loadings across currency portfolios. Its properties suggest that it is mainly important for capturing times-series variation in currency portfolio returns, while its contribution to cross-sectional pricing turns out to be economically small, albeit statistically significant. By contrast, the remaining factors are slope factors, as we can identify investment strategies for which the corner portfolios take factor loadings of opposite signs, with almost monotonic patterns across portfolios. Put simply, these latent factors behave as spread portfolios (which are long-short investment strategies), and therefore naturally connect to specific investment strategies. In particular, the second latent factor is strongly related to the Carry factor, while the third factor resembles the (short-term) Momentum factor.[5] The properties of the second and third latent factors – slope factors with high Sharpe ratios – suggest that they are crucial for cross-sectional pricing and take large weights in the SDF, which we find to be the case. The fourth factor seems to be a "long Value short (long-term) Momentum" factor, but it is not selected by any of the statistical criteria employed, consistent with the fact that its inclusion in the SDF improves only slightly the overall model pricing performance and Sharpe ratio.[6]

Therefore, this analysis ultimately shows that the currency SDF comprises at least three pricing factors that are closely related to the tradable Dollar, Carry, and Momentum factors, although it is important to note that the latent factors are not identical to these tradable factors. This means that the optimal-factor SDF cannot simply be replaced by a reduced-form SDF comprising Dollar, Carry and short-term Momentum (and Value) since these tradable factors are unable to span all the information in the latent factors which is required to price the full set of test-asset returns in our cross section.

Second, based on this optimal SDF, we turn to estimate the risk premiums of the non-

[4]However, it is important to note that the gain from using RP-PCA rather than PCA is smaller out of sample, which makes sense since RP-PCA is designed to maximize the in-sample Sharpe ratio.

[5]Short-term and long-term momentum strategies differ in that they use as sorting signals the one-month and one-year past returns, respectively. Menkhoff et al. (2012b) show that both of these strategies are profitable and imperfectly correlated, although short-term momentum generates higher expected returns.

[6]Throughout the paper, we term Dollar, Carry, Momentum and Value to refer to the tradable currency factors studied in the literature, whereas we use quotation marks ("Dollar", "Carry", "Momentum" and "Value") to refer to the first, second, third and fourth latent factors. Also, we often refer to the Dollar, Carry, Momentum and Value factors as tradable as opposed to the latent factors "Dollar", "Carry", "Momentum" and "Value", because the latter are not tradable in real time, even though they are convolutions of returns. This is because the latent factors are estimated using full sample information in our core analysis.

tradable candidate factors. This analysis is important as the optimal latent-factor SDF is only a first step to understand the economics of currency pricing, or asset pricing more generally. Ultimately, a key objective of macro-finance research is to understand the economic mechanism that drives the risk-return tradeoff (Cochrane, 2017), and the estimation of risk premiums for nontradable factors is meant to make progress in this direction. In our analysis, to start with, we find that the spanning regressions of the nontradable factors on the pricing latent factors deliver, on average, low R^2s. In the GX's framework, this would indicate that a large portion of nontradable candidate factors is due to measurement error. The problem is particularly severe for macro variables, while some of the text-based and, especially, of the financial factors are measured more precisely. In particular, text-based and financial factors are mainly exposed to the latent "Carry" factor, but some of these factors (mostly financial ones) also display significant exposures to the latent "Momentum" factor. Interestingly, the exposures of these candidate factors to the latent "Carry" and "Momentum" factors generally take opposite sign. This indicates that the two strategies respond to some of the same sources of financial risk, but in opposite ways. For example, when volatility increases "Momentum" tends to perform well, while "Carry" performs poorly, in line with what is observed during periods of markets turmoil, such as during the global financial crisis. This in turn implies that, if the latent "Momentum" factor is omitted from the SDF, the return-based (de-noised) candidate factors – the original nontradable factors cleaned from measurement error by converting them into return factors using a projection on the latent pricing factors – can display different behaviors and risk premiums. Finally, we note that the first latent factor, which behaves like a leveraged Dollar factor, is also statistically significant in driving some of the risk premiums (for financial factors) but its pricing contribution is economically small.[7]

We also show that the risk premiums obtained using the augmented three-pass method are substantially different from the FMB two-pass estimates. In fact, the two-pass method seems to deliver higher absolute point estimates and a larger number of candidate factors with significant risk premiums. This is not surprising given that inflated prices of risk are common among nontradable factors, exactly because they contain noise (Adrian et al., 2014). We document that the measurement-error problem is indeed pervasive also for a large number of our nontradable factors. Together with the omitted-variable problem, it can lead to biased risk-premium estimates and/or to erroneous selection of currency risk factors.

At the same time, thanks to the augmented three-pass method, we can also show that

[7]The Dollar factor in our paper is constructed using a broader cross section than typically used in the literature, covering both developed and a large number of emerging market currencies. The expansion of the currency universe allows us to estimate more precisely the Dollar risk premium, and to establish that it is statistically significant, albeit small, in our sample.

some nontradable factors have statistically significant risk premiums. The list of relevant factors is shorter than using the two-pass method, but it is still diverse. Some of the nontradable factors previously uncovered by the literature turn out to be less or even not relevant, but other "novel" factors (i.e., which were not considered in previous currency research) appear to have significant risk premiums, disclosing a tight link between currency and other financial markets that is mainly channeled through "Carry", in line with the conjecture of Koijen et al. (2018). In particular, our findings highlight the relevance of uncertainty and volatility measures (both financial and text-based) and of liquidity factors to explain currency returns. Specifically, the global volatility factor of Menkhoff et al. (2012a) and the global Economic Policy Uncertainty (EPU) of Baker et al. (2016) are singled out, as their risk premiums are large and precisely estimated. Moreover, the signs of the risk-premium estimates of the financial and text-based factors appear intuitively clear. Factors that perform poorly (well) in bad states of the world command positive (negative) currency risk premiums, and hence are procyclical (countercyclical) factors, based on the three-pass estimator.

However, the results point to a substantial disconnect between currency returns and macroeconomic variables, which is disappointing as it is hardly imputable to their measurement error given that the three-pass method accounts for that. Moreover, even among the few macro variables with weakly significant premiums estimates, some display risk premiums with counterintuitive signs. We then show that the disconnect is not the consequence of macro variables being weak factors (i.e., factors that are relevant only for a subset of the test assets). In fact, we find similar results using the supervised principal component analysis (SPCA) estimator, recently developed by Giglio et al. (2021c) to explicitly tackle the issue of weak candidate factors in the estimation of factor risk premiums. Moreover, the SPCA results show that even the few macro variables with significant risk premiums can be very poorly hedged out of sample using currency portfolios. As a result, the disconnect between macro variables and currency portfolio returns is confirmed using SPCA. We show that these results hold in a number of robustness checks and additional analysis.

Finally, we verify through a simulation exercise that the augmented three-pass method works well also in finite samples that match the dimension and properties of the FX portfolio returns in our paper. This analysis also shows that both the omitted-variable and measurement-error problems can be material in the estimation of currency risk premiums, in a similar way as documented by GX for equity markets. This evidence gives us further comfort that the methods employed here are both reliable and desirable for our purposes, and that the unconditional three-pass model, if well specified, provides a satisfactory description of dynamically rebalanced FX portfolio returns.

The closest paper to ours is independent work by Chernov et al. (2022), which tackles similar objectives to the ones targeted in our paper, in a very different way. Specifically, Chernov et al. (2022) address the question of the optimal factor model for pricing currency risk, which relates to the first goal of our paper. They do so by studying directly the mean-variance efficient portfolio, and relying on the conditional projection of the SDF onto excess returns of individual currencies. They show, in the context of G10 currencies, that this approach allows to price individual currencies and several canonical strategies (derived from carry, momentum, and value signals), both conditionally and unconditionally. On the one hand, this approach has the advantage, relative to the methods adopted in our paper, that currency pricing is carried out more directly since the estimated SDF is represented as a linear function of the unconditional mean-variance efficient portfolio. On the other hand, working directly with the mean-variance efficient portfolio can only be achieved on a set of assets that is small enough to allow reliable estimation of the covariance matrix of currency returns, which is the case in the paper by Chernov et al. (2022). Moreover, one has to take a stand on the set of factors or signals that drive the conditional mean. In turn, this exposes the approach to potential omitted-variable problems (in addition to potential measurement-error problems), which are instead taken into account using the GX three-pass methods employed in our paper. Ultimately, we view the study of Chernov et al. (2022) as complementary to our paper.

2 Asset Pricing Methods

The FMB two-pass method has long represented the workhorse model to estimate risk premiums in empirical asset pricing (see a brief description of FMB in the Internet Appendix, Section I). In currency asset pricing, it is widely employed at least since the influential study of Lustig and Verdelhan (2007). Over the years, some fixes to the original two pass-procedure have been proposed, and they mainly regard the efficiency of the estimates, which relates to the use of the generated risk-exposure covariates in the second-pass regression (e.g., Shanken, 1992; Burnside, 2011). By contrast, the omitted-variable and measurement-error problems have received less attention.

The *omitted-variable* problem arises when (some of) the relevant risk factors are omitted from the SDF. This omission biases the estimates of the risk exposures in the first pass, and the estimates of the prices of risk in the second pass. As a result, the researcher attributes the effect of the missing factors/exposures to the estimated effect of the included factors/exposures. In the first pass, the severity of the bias depends on the time-series correlation between the factors included and those omitted. In the second pass, it varies with the cross-sectional correlation of the estimated exposures and the missing exposures associated with the omitted factors. The *measurement-error* problem instead emerges even when the researcher includes all the 'true' risk factors in the SDF, but the factors are measured with noise. This problem is particularly severe in the case of nontradable factors, especially those based on macroeconomic variables. The use of noisy factors may bias the first-pass estimates of the risk exposures and, as a consequence, the second-pass estimates of the prices of risk.

Both problems can manifest in many situations. A clear example is when the researcher wants to estimate the price of risk of a novel nontradable factor g_t, λ_g. In principle, the standard FMB procedure is viable but the researcher would need to (i) know the set of control factors, i.e., the set of 'true' factors entering the SDF, f_t; and (ii) use factors that are cleaned, i.e., measured without noise. By contrast, the three-pass method of GX delivers an estimate of the price of risk of the candidate factor that is not affected by (i) and (ii). To do so, the GX method exploits the information in the test assets, by projecting the candidate factor onto the space of the latent pricing factors implied in the cross section of test-asset returns. In this way, one can remain agnostic about the set of 'true' risk factors, and yet obtain an estimate of λ_g that is not affected by the omitted-variable problem. Moreover, one can easily account for the measurement error in the candidate factor.

While GX employ standard PCA to extract the latent pricing factors, one can recur to other methods to estimate the factors and still exploit in full the benefits of the three-pass method. Recently, LP developed the RP-PCA estimator. A benefit of this novel method is that the latent factors are estimated such that they fit both the time series and cross section of expected returns. Conversely, standard PCA neglects the information in the means of the portfolio returns. We therefore combine the RP-PCA method of LP with the three-pass method of GX, and this is why we call it the augmented three-pass method.

2.1 (Augmented) Three-Pass Method

Before turning to the three-pass method of GX, we first present the RP-PCA method that we use to extract the factors from the panel of currency returns and the evaluation criteria employed to shed light on the optimal currency SDF.

2.1.1 Latent Factors Estimation

To start with, we assume that K factors capture the systematic component of asset returns and the unexplained idiosyncratic component subsumes the asset-specific risks, such that

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

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

$$\mathrm{Var}(X) = \psi \mathrm{Var}(\mathrm{F}) \psi^\top + \mathrm{Var}(\epsilon), \tag{2}$$

which consists of a systematic part and an idiosyncratic part. Standard PCA exploits the fact that the factors relate to the largest eigenvalues of $\mathrm{Var}(X)$, which can be retrieved from the sample covariance matrix of excess returns

$$\Sigma_{\mathrm{PCA}} = \frac{1}{T} X^\top X - \overline{X}^\top \, \overline{X}, \tag{3}$$

where $\overline{X}$ denotes the sample mean of excess returns.

The estimated factor loadings $\hat{\psi}$ are proportional to the eigenvectors associated with the largest eigenvalues of Σ_{PCA}. The factors $\hat{F}_t$ are then obtained by regressing the asset returns on the factor loadings. Thus, factors extracted by PCA minimize the unexplained time-series variation of the returns. Evidently, however, the information in the means of the returns is not accounted for. LP note that, in the context of asset pricing, this implies ignoring valuable information, as the role of the means is explicitly given by Ross' arbitrage pricing theory (APT).[8] Asset pricing factors should capture the information contained both in the first and second moments of test-asset returns. For this reason, LP propose to apply PCA to a covariance matrix with overweighted sample mean returns; in essence, RP-PCA is a generalized version of PCA regularized by a pricing-error penalty term, which is tantamount

[8] Under the strong form of APT, residual risk has a risk premium of zero, which holds without loss of generality when assets are portfolios. An asset excess return is then given by its exposures to the factors times the factors' risk prices. Moreover, if the factors are excess returns, no-arbitrage implies that their means are the factors' prices of risk. Hence, the means are informative about the assets' risk premiums.

to applying PCA to the covariance matrix

$$\Sigma_{\text{RP}} = \frac{1}{T} X^\top X + \omega \, \overline{X}^\top \, \overline{X}, \tag{4}$$

where ω is the penalty term, or RP-weight. As before, the factors are constructed by regressing the returns on the factor loadings, i.e., $\hat{F} = X\hat{\psi}(\hat{\psi}^\top \hat{\psi})^{-1}$. However, the loadings $\hat{\psi}$ are now proportional to the eigenvectors associated with the largest eigenvalues of the Σ_{RP} matrix. Intuitively, in RP-PCA, the eigenvalues relate to a generalized notion of "signal strength" of a factor, while in PCA the eigenvalues are equal to the factor variances, exactly because the information in the portfolio means is neglected. That is, the matrix Σ_{RP} should converge to

$$(\Sigma_F + (1+\omega)\mu_F^\top \mu_F)\psi^\top + \text{Var}(\epsilon), \tag{5}$$

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

$$\min_{\psi, F} \underbrace{\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{nt} - F_t \psi_n^\top)^2}_{\text{TS unexplained variation}} + \omega \underbrace{\frac{1}{N} \sum_{i=1}^{N} (\overline{X}_n - \overline{F}\psi_n^\top)^2}_{\text{CS pricing error}}, \tag{6}$$

where $\overline{F}$ is the vector of factor expected values. From Eqs. (4)-(6), it is clear that RP-PCA with $\omega = -1$ is equivalent to standard PCA as it forgoes the information in the means. Also note that RP-PCA with $\omega = 0$ corresponds to applying PCA to the second-moment matrix instead of a covariance matrix. Conversely, RP-PCA with $\omega > 0$ can be interpreted as PCA applied to a matrix that "overweights" the information in the means. That is, RP-PCA combines two moment conditions, pushing up the signal-to-noise ratio and therefore leading to more efficient estimates of the factors. It selects factors that explain the time series, but at the same time penalizes factors with low Sharpe ratios. This is because factors that help price the cross section of asset returns have non-vanishing returns and higher Sharpe ratios. Thus, RP-PCA with $\omega > 0$ may help detect weak factors if they have high Sharpe ratios, exactly because the weak signal in their variances is enhanced by the information in their means. Meanwhile, it protects from selecting spurious factors (i.e., factors with vanishing loadings), as it requires the estimated factors to explain a substantial amount of time-series variation.

Evaluation Criteria. The spectrum of the estimated eigenvalues is informative about the factors' "signal strengths" and, hence, can help determine the optimal SDF. One can establish how many factors are relevant, as well as discern strong from weak factors. Statistical tests such as the ones used by LP and GX are useful in this regard.[9] Importantly, a by-product of the LP method is that factors retain a clear economic interpretation, as factors extracted using RP-PCA are return-based with unrestricted means. In fact, one can rely on several intuitive metrics to complement the evidence resulting from statistical tests. In this way, the choice of the optimal SDF is guided by both statistical and economic criteria.

A clear object of interest is the maximal Sharpe ratio 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 $\hat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$ is a 1 × K vector; the $\hat{b}_{MV}$ entries capture the factor weights in the implied SDF, $\varphi_t = 1 - (\hat{F}_t - \mu_F)\hat{b}_{MV}^{\top}$.[10] Two further diagnostic criteria – the root-mean-square error ($\overline{RMS}_\alpha$) and the magnitude of the idiosyncratic variance ($\overline{\sigma}_\epsilon^2$) – are useful to evaluate the model performance, inform the choice of the penalty value ω, and determine which factors to include in the SDF. Such criteria are centered around the estimation of ordinary least squares (OLS) time-series regressions

$$X_{nt} = \alpha_n + \hat{F}_t \; {}_n^{\top} + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{7}$$

where the intercept α_n captures the magnitude of the asset-specific pricing errors. Put simply, Eq. (7) is the OLS counterpart of the factor model of Eq. (1), but differs for two main reasons. First, it includes the intercept, while the factor model imposes no intercept and hence the residuals have means that are not necessarily zero. Second, the OLS regression (without intercept) and the factor model yield the same estimates of ψ_n only when RP-PCA uses $\omega = 0$. This is because the pricing-error term of Eq. (6) drops out, and hence the two methods minimize the same objective function.[11] Nevertheless, LP argue that the difference turns out to be negligible in the data. Thus, one can use Eq. (7) to compute $\overline{RMS}_\alpha = \sqrt{\hat{\alpha}\hat{\alpha}^{\top}/N}$, and $\overline{\sigma}_\epsilon^2 = \frac{1}{N}\sum_{n=1}^{N}\left[Var(\hat{\epsilon}_n)/Var(X_n)\right]$ implied by $\hat{F}$. Note that these two statistics should move in opposite direction as the penalty ω varies; *ceteris paribus*, for higher values of the penalty, the pricing error should diminish at the cost of higher variance of the idiosyncratic component. Hence, based on these statistics, one can evaluate

[9] In order to determine the optimal number of latent factors to include in the SDF, LP use the test of Onatski (2010), whereas the GX's estimator is based on a penalty function similar to the one of Bai and Ng (2002). The Onatski (2010) test relies on the idea that the eigenvalues associated with the systematic factors diverge to infinity, while the eigenvalues associated with idiosyncratic factors cluster around a single point. Put simply, the eigenvalues of systematic factors should be separated from those of weak factors.

[10] If the estimated factors are orthogonal, Σ_F is diagonal and $\hat{b}_{MV}$ is a vector with entries $\hat{b}_{MV,k} = \mu_{F,k}/\sigma_{F,k}^2$, where $\mu_{F,k}$ and $\sigma_{F,k}^2$ denote the k-th factor's estimated mean and variance. We follow common practice and search for a small number of factors whose linear combination with constant loadings in the SDF prices assets unconditionally.

[11] RP-PCA with $\omega = -1$ yields the same estimates of Eq. (7) applied to demeaned X_{nt} and $\hat{F}_t$. LP show that, also for $\omega > 0$, RP-PCA loadings can be retrieved using OLS regressions. We return to this issue in the next section.

the trade-off, and pin down the optimal value of the RP-weight, ω.

2.1.2 Candidate Factor Price of Risk Estimation

So far, we showed how to efficiently estimate the latent factors, and how to select the factors entering the optimal SDF. All of this is instrumental to apply the GX three-pass method to obtain accurate estimates of the candidate factors' risk premiums, which we present next.

1. `Test-Asset Exposures to Latent Factors` (ψ). The first pass consists of estimating test-asset risk exposures to latent factors. Because GX use PCA to extract the latent factors, they obtain the risk exposures through time-series OLS regressions of test-asset excess returns on the latent factors. As mentioned earlier, this is no longer exact when the factors are extracted using RP-PCA with $\omega > 0$. However, the exposures ψ implied in the factor model of Eq. (1) can still be recovered using OLS regressions. To do so, one has to transform the excess return data and the factors in such a way to incorporate the information of the pricing errors. Specifically, the time-series OLS regressions become

$$\tilde{X}_{nt} = \tilde{F}_t \;\; {}_n^{\top} + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{8}$$

where $\tilde{X}_{nt} = X_{nt} + \tilde{\omega}\bar{X}_{nt}$, and the vector $\tilde{F}_t$ contains elements defined as $\tilde{F}_{kt} = \hat{F}_{kt} + \tilde{\omega}\bar{F}_{kt}$ for $k = 1, \ldots, K$, with $\tilde{\omega} = \sqrt{\omega + 1} - 1$. In this way, the RP-PCA risk exposures can be retrieved for any value of ω.

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

$$\overline{X}_n = \hat{\psi}_n \gamma^{\top} + a_n, \quad n = 1, \ldots, N, \tag{9}$$

where γ is the $1 \times K$ vector of the latent factor prices of risk.[12]

3. `Candidate Factor Price of Risk` (λ_g). The last pass of the GX procedure yields the price of risk 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

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

candidate factor innovation, g_t^ι, on the demeaned latent factors, $\hat{F}_t^\iota = \hat{F}_t - \mu_F$, as follows

$$g_t^\iota = \hat{F}_t^\iota \eta^\top + u_t, \tag{10}$$

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

$$\hat{\lambda}_g = \hat{\gamma}\hat{\eta}^\top, \tag{11}$$

$$\hat{g}_t = \hat{F}_t\hat{\eta}^\top, \tag{12}$$

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

`Rotation Invariance of Risk Premia`. Before turning to the empirical analysis, it is important to introduce the rotation-invariance result shown in GX. The main result is that the risk-premium estimate of a candidate factor is rotation invariant, as its estimate does not change when the model is expressed as a function of rotated factors, $\hat{\hat{F}}_t \equiv \hat{F}_t H^{-1}$, for any full-rank $k \times k$ matrix H, instead of the original factors $\hat{F}_t$. In essence, a parameter (or quantity) is rotation invariant if it is identical in the original model or in any rotated model (Giglio and Xiu, 2021). Specifically, defining $\hat{\hat{\gamma}} \equiv \hat{\gamma}H^{-1}$ and $\hat{\hat{\eta}} \equiv \hat{\eta}H^\top$, it holds that

$$\hat{\lambda}_g = \hat{\gamma}\hat{\eta}^\top = \hat{\gamma}H^{-1}H\hat{\eta}^\top = \hat{\hat{\gamma}}\hat{\hat{\eta}}^\top. \tag{13}$$

Importantly, neither γ nor η by itself is rotation invariant, because $\hat{\hat{\gamma}} \equiv \hat{\gamma}H^{-1} \neq \hat{\gamma}$ and $\hat{\hat{\eta}} \equiv \hat{\eta}H^\top \neq \hat{\eta}$. Similarly, the risk exposures of assets to the rotated factors differ from the exposures to the original factors ($\hat{\hat{\psi}}_n \equiv \hat{\psi}_n H^\top \neq \hat{\psi}_n$). Thus, unless one knows the rotation matrix H, not all original parameters can be recovered. Yet, even without knowing H, any consistent estimator of $\hat{\hat{\gamma}}\hat{\hat{\eta}}^\top$ will consistently estimate the candidate factor risk premium, $\hat{\lambda}_g$.

3 Test Assets and Factors

In this section, we first describe the exchange rate data, and explain how excess returns are computed. We then present the currency portfolios (test assets), and the nontradable macro-financial factors (candidate risk factors).

3.1 FX Data and Excess Returns

FX Data. We collect spot exchange rates and one-month forward rates vis-à-vis the U.S. dollar (USD) from Barclays and Reuters, available 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), that is, USD/FCU. Hence, an increase in the exchange rate corresponds to an appreciation of the foreign currency. The empirical analysis is based on monthly data obtained by sampling end-of-month FX rates from October 1983 to December 2017. Our sample covers 49 currencies, of which 15 are regarded as developed countries following standard definitions in prior literature (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). However, the sample size is not fixed, given that it varies over time as data for some currencies are not available from October 1983, or some currencies cease to exist due to the adoption of the euro. That is, we work with an unbalanced panel of individual currencies. We provide detailed information on the FX data in the Internet Appendix (Section II).

FX Excess Returns. Currency excess returns are defined as follows

$$X_{it+1} = \frac{S_{it+1} - F_{it}}{S_{it}}, \tag{14}$$

where, using notation local to this subsection, F_{it} is the forward exchange rate that matches the spot exchange rate S_{it} for currency i (Bekaert and Hodrick, 1993). According to Eq. (14), the excess return results from buying the foreign currency in the forward market at time t, and selling it in the spot market at time $t+1$. As a matter of convenience, throughout this paper we refer to the forward premium $fp_{it} = \frac{S_{it}-F_{it}}{S_{it}} \approx i_{it} - i_t$ as either the forward premium or interest rate differential relative to the U.S. dollar, with i_{it} and i_t denoting the foreign and U.S. interest rate, respectively. Indeed, under covered interest parity (CIP), the interest rate differential is equal to the forward premium (Akram et al., 2008).[13]

3.2 Test Assets

A large cross section of test assets is central to the validity of the GX three-pass method (Giglio and Xiu, 2021). Our test assets are currency portfolios rather than individual currencies. By using portfolios, we can average out idiosyncratic components of currency returns

[13] As is usual in the literature, we compute FX excess returns using forward rates rather than interest rate differentials for two main reasons. First, marginal investors (such as, e.g., hedge funds and large banks) that are responsible for the determination of exchange rates trade mostly using forward contracts (e.g., Koijen et al., 2018). Second, for many countries, forward rates are available for much longer time periods than short-term interest rates. It is reasonable, however, to exclude the months when CIP is strongly violated; in doing so, we follow Kroencke et al. (2014) and Della Corte et al. (2016b), among others (see Section II, in the Internet Appendix).

and focus only on their systematic risk (Cochrane, 2005). Moreover, portfolios dynamically include individual currencies as their returns and signals become available, resulting in a balanced panel of test assets.

We consider currency portfolios associated with widely-used trading strategies. Overall, the baseline sample consists of $N = 46$ currency portfolios that stem from nine popular investment strategies: carry (e.g., Lustig et al., 2011; Menkhoff et al., 2012a), short-term and long-term momentum (e.g., Asness et al., 2013; Menkhoff et al., 2012b), currency value (e.g., Asness et al., 2013; Kroencke et al., 2014; Menkhoff et al., 2017), net foreign assets and liabilities in domestic currencies (Della Corte et al., 2016b), term spread (Bekaert et al., 2007; Lustig et al., 2019), long-term yields (Ang and Chen, 2010), and output gap (Colacito et al., 2020). In what follows, we refer to these strategies as Carry, ST and LT Mom, Value, NFA, LDC, Term, LYld, and GAP, respectively.[14]

We provide a detailed description of each investment strategy in the Internet Appendix (Section II); 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 similar. In fact, all strategies are tradable and rest on single sorts (with the exception of LDC, which uses double sorts on net foreign assets and the proportion of foreign currency denomination of liabilities). At time t, currencies are allocated to NP portfolios using the past signal for the selected strategy. Then, for a generic portfolio n, the excess returns realized between time t and $t+1$, X_{nt+1}, are computed as the equally-weighted average of the individual currency excess returns allocated to that portfolio. In line with most of the FX literature, we use $NP = 5$ for single-sorted portfolios. By construction, as we move from portfolio 1 (P1) to portfolio 5 (P5), the portfolios should contain currencies with increasing riskiness. Hence, if the risk-return trade-off holds, the spread portfolio (HML) – the return difference between P5 and P1 – should give a positive return because P5 contains currencies with high risk, whereas P1 includes currencies with low risk.

3.3 Nontradable Candidate Factors

We now turn to the nontradable (or non-return-based) candidate risk factors for which we aim at estimating the price of risk. These factors feature in the last pass of the GX three-pass method (see Section 2.1.2), which is implemented separately for each candidate factor. Therefore, the choice of a candidate factor does not affect the analysis of the other factors

[14] We choose these test assets with the aim of analyzing monthly currency strategies over a long time period and broad currency universe. This means that we do not include option-based strategies, which are available for a much shorter sample (e.g., Della Corte et al., 2016a; Della Corte et al., 2021), and strategies based on FX order flows and volumes, which are typically studied at the daily frequency (e.g., Menkhoff et al., 2016; Cespa et al., 2022; Ranaldo and Somogyi, 2021).

or the optimal SDF.

To begin with, we consider a reasonably long list of macro factors. In this way, we shed light on the link between the macroeconomy and asset returns, which is a central issue in macro finance (Cochrane, 2017). While the link is clear in theory, it is hard to establish empirically. Currency returns are no exception in this regard, and the disconnect is possibly even more evident than in other financial markets. In theory, currency returns and macro fundamentals are tightly linked together (e.g., Hassan, 2013; Gabaix and Maggiori, 2015; Ready et al., 2017; Berg and Mark, 2018a). In reality, the link between the two is weak (Meese and Rogoff, 1983; Mark, 1995), or highly unstable (Rossi, 2013; Fratzscher et al., 2015). A recent finding, however, is that macro fundamentals seem to be strongly connected to the *cross section* of currency returns (e.g., Colacito et al., 2020; Dahlquist and Hasseltoft, 2020). That said, macro fundamentals are often poorly measured and are clearly nontradable factors, so that both sources of bias that we address in this paper are likely to be sizable.

We also consider another set of nontradable factors that is gaining momentum in the asset pricing literature, which pertains to financial conditions. The global financial crisis has spurred an extensive literature on volatility and liquidity risks (e.g., Lustig et al., 2011; Menkhoff et al., 2012a; Karnaukh et al., 2015), uncertainty shocks (e.g., Bekaert et al., 2013; Dew-Becker et al., 2017), and the leverage of financial intermediaries (e.g., Adrian et al., 2014; He et al., 2017). These factors are also nontradable, and their measurement is often imprecise. Furthermore, some of these measures are global, while others focus on the U.S. market. Most measures are specific to equities and bonds, but there is by now overwhelming evidence that financial and uncertainty shocks can easily propagate across markets. We therefore attempt to capture such complexity by using multiple popular measures of (il)liquidity, volatility, and uncertainty.

In addition to macro and financial variables, we also extend the analysis to the recently developed text-based factors, which are obtained by aggregating into an index news coverage about specific sources of uncertainty. Text-based indicators based on news coverage of policy uncertainty and, more recently, of equity market volatility are becoming increasingly prominent in the literature (e.g., Baker et al., 2016; Baker et al., 2019). Their sub-categories are also particularly informative about asset returns (e.g., Giacoletti et al., 2021). We therefore estimate also the risk premiums of many text-based factors. By doing so, we broaden the measurement of macro-financial risks.

Taken together, the list of nontradable candidate factors consists of a total 134 factors, which we find useful to group as financial (24), text-based (30), and macro (80). However, the following additional observations are in order. First, the set of factors is comprehensive but by no means exhaustive, mainly because some factors are not available at the monthly frequency. Second, the distinction across categories is largely adopted for convenience, not being exact for some factors, especially for those capturing multiple sources of risks. For example, macro risk is captured not only through the raw macro variables, but also through some of the text-based and possibly financial factors.[15] In this sense, we do not view these variables as separate and *true* risk factors (also because they are measured with error), rather as macro-financial variables that relate to the 'true' factors. Finally, as is common in the asset pricing literature (Merton, 1973), we do not use the factors as such but we first convert them into innovations, capturing the unexpected changes in the factors (in the baseline analysis, we simply use the residuals from AR(1) processes as, e.g., in Menkhoff et al., 2012a). A brief overview of the candidate factors and more detailed motivations for selecting them are provided in the Internet Appendix (Section III).

4 Empirical Analysis

In this section, we present the main findings of the empirical analysis. To start with, we assess the cross section of portfolio currency returns using descriptive statistics (Section 4.1). We then present the RP-PCA estimates of the latent factors and shed light on the properties of the optimal currency SDF (Section 4.2). Next, we turn to the three-pass estimates of the risk premiums of the nontradable candidate risk factors (Section 4.3). Finally, we present a number of robustness checks, additional analysis on the stability of the factor structure, and estimates obtained using alternative methods that account for the possibility that some of the candidate factors are weak (Section 4.4).

4.1 Currency Portfolios

Table A3, in the Internet Appendix, presents summary statistics of the currency portfolios, i.e., our test assets, associated with the nine investment strategies described in Section 3.2. We find that 22 out of 46 individual portfolios deliver statistically significant returns. Importantly, all strategies deliver spread HML portfolios (denominated as CS in Table A3 as these are cross-sectional portfolios) with positive and statistical significant average returns, with the exception of the LYld HML portfolio. Since HML portfolios are self-financed long-short strategies, they represent U.S. dollar-neutral strategies. Moreover, for these HML portfolios the average excess return is the price of risk, given that it has unit exposure by construction. Therefore, the average return of the HML portfolio is a key statistic to look

[15]For instance, the latent factors of Jurado et al. (2015) are placed in the group of financial factors, but they also contain macroeconomic information. Similarly, some text-based factors measure uncertainty related to the macroeconomic environment.

at. Carry, ST Mom and GAP HML portfolios yield the highest expected excess returns (7.3, 6.9, and 6.7 percent per annum, respectively), while LYld and Term HML portfolios display the lowest excess returns (1.9 and 2.8 percent per annum, respectively).

We then resort to an intentionally simple exercise to visually illustrate the risk-return trade-off inherent in the currency portfolios. Figure 1, top panel, shows that "low-signal" portfolios (P1, P2) tend to be mostly placed in the bottom left-hand corner (low risk/ low return), whereas "high-signal" portfolios (P4, P5) in the top right-hand corner (high risk/high return). In short, with few exceptions, higher returns seem to compensate for higher risks, which is consistent with the existence of a risk-return trade-off in currency portfolios. In the bottom panel, we instead present the time series of HML portfolios' cumulative returns, which clearly show the stronger performance of Carry, ST Mom and GAP investment strategies, but also that the underlying sources of risk differ. For example, during the global financial crisis ST Mom strongly outperforms Carry.

Pair-wise correlations among HML portfolios (Table A4, in the Internet Appendix) are also of interest, as they provide a first piece of suggestive evidence on the factor structure of the optimal currency SDF. Above all, Carry appears to be a dominant strategy, as not only it yields the highest returns, but it also correlates positively with many other strategies. LYld and, to a lower extent, Term portfolios strongly correlate with Carry (76 and 54 percent, respectively), but on the backdrop of substantially lower returns than Carry. The global imbalances HML portfolios, LDC and NFA, also appear to be tightly linked to Carry. Hence, Carry singles out as a pervasive strategy. Moreover, and perhaps not surprisingly given that the signals of both strategies depend on past returns, the excess returns of ST and LT Mom portfolios are positively related, but their correlation is not particularly high (around 25 percent), possibly due to mean reversion in returns. However, in absolute terms, the LT Mom spread portfolio co-moves mostly with the Value portfolio (around –39 percent). Also, in line with the extant literature (e.g., Koijen et al., 2018), we find that momentum strategies have low correlation with Carry, suggesting that they may be driven by a separate risk factor. Similarly, the GAP strategy exhibits a high risk premium, and yet displays particularly low correlations with respect to the other strategies.

In sum, while some strategies are strongly related, others are weakly or even negatively related, suggesting that multiple sources of risk drive currency portfolio returns. It is, however, ex-ante unclear how many slope risk factors – other than Carry – are needed to capture the risk-return trade-off in the FX market. Next, we assess more formally the structure of the optimal latent-factor currency SDF.

4.2 Currency Pricing Kernel

To begin with, we extract the latent factors from the panel of currency portfolio returns using different values of the RP-weight.[16] We contrast the estimates from models using PCA with those from models using RP-PCA with higher and increasing values of the RP-weights. These models could differ in terms of the detection of the factors, the factor compositions, and the order of the factors. To highlight differences across models, we first assess the factor "signal strengths", also recurring to statistical tests. We then complement this statistical information with the model diagnostics, based on the three economic evaluation criteria presented in Section 2.1.1, to better determine the dimension and properties of the SDF. Next, we present the main results, while the more detailed analysis of the latent factor "signal strengths" and, relatedly, of the SDF are presented in the Internet Appendix (Section IV). Finally, we try to link the extracted latent pricing factors to the observable currency strategies.

`Latent Factor "Signal Strengths".` As explained in Section 2.1.1, the ability to detect a pricing factor depends on the factor's signal-to-noise ratio. In RP-PCA, the "signal strength" of a factor is captured by the associated eigenvalue of the matrix $(\frac{1}{T}X^\top X + \omega\bar{X}^\top\bar{X})$, call it Σ_{RP}. To begin the SDF analysis, it is therefore useful to inspect the behavior of the largest eigenvalues of Σ_{RP}, both plain and normalized by the idiosyncratic variance, as the latter more closely relate to the signal-to-noise ratio. At the same time, it is useful to assess what drives a factor's overall "signal strength", by simply inspecting its composition. In this way, we try to establish whether a factor (i) is strong or weak, and (ii) with high or low Sharpe ratio. We report this (and additional) evidence in Table A8, and present the main results in what follows.[17]

The first eigenvalue is large and hence is symptomatic of a systematic, strong factor. On the contrary, the remaining eigenvalues are substantially smaller, so that the associated factors are consistent with a weak-factor interpretation (i.e., factors that explain only a subset of test assets). This evidence is qualitatively similar when using either PCA or

[16]Both PCA and RP-PCA require a balanced panel of test-asset returns. To fill the few missing observations in test-asset returns X (GAP portfolios are available only until January 2016), we use the nuclear-norm penalized regression approach, recently employed by Giglio et al. (2021b), to which we refer for more details on the procedure. We find that the main empirical results are robust to the method used to recover X, for example if we replace the missing returns with the sample mean of returns (which we did in a previous draft of this paper).

[17]In the empirical analysis, we limit the focus to the six largest eigenvalues/factors, as the remaining eigenvalues have negligible "signal strengths". Also note that, following LP, we normalize the loadings such that the factors are orthogonal with each other and have different means and variances. Specifically, we adopt the Gram-Schmidt method, which has the benefit of orthogonalizing the factors sequentially. The models based on the original and orthogonal factors are observationally equivalent. Factors are orthogonalized mainly to facilitate their economic interpretation, e.g., regarding their distinct contributions to the currency SDF.

RP-PCA to estimate the factors. However, by employing the latter method (and with reasonably high RP-weights), it is evident that factors' "signal strengths" are enhanced, factors are better separated from each other, and the information is aggregated in a small number of factors. In doing so, RP-PCA helps us estimate the factors more efficiently, as documented also by LP for characteristic-sorted stock portfolio returns.

In particular, we find that RP-PCA enables us to detect weak factors with high Sharpe ratios, which are missed by standard PCA. The third factor is a clear example in this regard. In fact, the O and GX tests point to a two-factor SDF when the factors are extracted using PCA, and to a three-factor SDF when using RP-PCA (Figure 2 shows the eigenvalues and the results of the tests for different models). This is exactly because RP-PCA overweights the sample mean returns, and hence enhances the *overall* "strength" of the factor, on the backdrop of essentially unchanged *time-series* "strength". Put simply, the third factor extracted via RP-PCA appears to be a weak factor but with high Sharpe ratio (or risk premium). These types of factors are particularly hard to identify, and yet have important asset pricing implications, exactly because of their large risk premiums. Thus, their omission is likely to distort the candidate factor risk-premium estimates.

Using RP-PCA, also the fourth factor qualifies as a weak pricing factor, given that it has a positive and significant risk premium (see Table A8). Indeed, $\hat{F}_4$ behaves qualitatively like $\hat{F}_3$, but its Sharpe ratio is only about half of that of $\hat{F}_3$ (despite the two factors having comparable time-series "strengths"). This suggests that the pricing contribution of $\hat{F}_4$ is not sufficient to increase its signal-to-noise ratio in a way that $\hat{F}_4$ is selected by the statistical tests.[18] The remaining factors have zero risk premiums, and hence are weak time-series factors.

Therefore, based on the "signal-strength" analysis, the optimal SDF should include at least the first three pricing factors extracted via RP-PCA. Next, to complement the above evidence, we proceed with the analysis of the other evaluation criteria to better inform the choice of the RP-weight. By doing so, we also try to further characterize the properties of the optimal latent-factor currency SDF, going beyond its dimension.

Optimal Currency SDF ($\varphi(F_K^{\omega})$). The selection of the RP-weight responds to the dual objective of achieving a model with good pricing performance and high SDF maximal Sharpe ratio (SR), while preventing idiosyncratic variance from increasing too much (e.g., Lettau and Pelger, 2020b). Therefore, in theory, there might be a trade-off such that higher (lower) RP-weights imply lower (higher) pricing errors (e.g., $\overline{RMS_\alpha}$) at the cost of higher (lower)

[18]However, consistently with GX, we will show in simulation that these tests tend to underestimate the true number of factors in finite samples. Hence, the evidence resulting from these tests needs to be taken with caution.

idiosyncratic variance ($\overline{\sigma}_\epsilon$). We evaluate the trade-off for a range of RP-weights in Table 1. The results are clear-cut: there is virtually no evidence of trade-off in choosing RP-PCA over PCA (in line with the "signal-strength" analysis of Table A8).

Specifically, the idiosyncratic variance increases only slightly with the RP-weights, while the reduction in the pricing errors is substantial (Panel A). However, the marginal gains in terms of pricing performance obtained by using very large RP-weights are small. In fact, pricing-error statistics tend to stabilize for $\omega \geq 20$, and we do not see additional benefits in using RP-weights higher than 20. This choice of the RP-weight is further corroborated by the analysis of the maximal SRs (Panel B), which tend to level off for $\omega \geq 20$. Moreover, the SR of the three-factor SDF obtained with $\omega = 20$ is 1.57, while it drops to 0.90 using $\omega = -1$.[19] Such a wedge is almost equally due to $\hat{F}_2$ and $\hat{F}_3$ when moving from $\omega = -1$ to $\omega = 20$. By adding $\hat{F}_4$ to the SDF, the SR further increases to 1.65 using RP-PCA with $\omega = 20$, while is unchanged using PCA. Therefore, with $\omega = 20$ $\hat{F}_4$'s contribution to the maximal SRs is quite small, while the contributions of $\hat{F}_5$ and $\hat{F}_6$ are nil.

By looking at the SDF-weights the distinction becomes more apparent between time-series and cross-sectional pricing factors, as only the latter take non-zero weights in the SDF and contribute to price currency portfolios. Specifically, using RP-PCA with $\omega = 20$, $\hat{F}_2$ and $\hat{F}_3$ take by far the largest weights in the SDF, followed by $\hat{F}_4$. Nevertheless, the pricing contribution of $\hat{F}_4$ is much smaller than that of the other two weak pricing factors (i.e., $\hat{F}_2$ and $\hat{F}_3$). This, combined with the fact that $\hat{F}_4$ adds little to the maximal Sharpe ratio, helps explain why it is not selected by the statistical tests. The SDF-weights of $\hat{F}_5$ and $\hat{F}_6$ are also small, which corroborates our previous evidence showing that they are weak time-series factors. The SDF-weight of $\hat{F}_1$ is also small, but $\hat{F}_1$ is a strong factor with a statistically significant mean and a non-trivial Sharpe ratio. Thus, the role of $\hat{F}_1$ is primarily that of a strong level factor as its pricing contribution, albeit not negligible, is much less relevant than that of $\hat{F}_2$ and $\hat{F}_3$ (we will lend further support to this interpretation using additional evidence later in the paper).[20]

Taken together, this analysis suggests that the optimal latent-factor currency SDF should consist of at least three (and potentially four) factors, and an RP-weight of 20 seems a

[19] Such difference becomes even starker if one compares the respective optimal SDFs; in fact, the SR of $\varphi(F_{1-3})$ with $\omega = 20$ is over three times higher than the SR of $\varphi(F_{1-2})$ with $\omega = -1$. We find qualitatively similar evidence for the pricing errors. Thus, RP-PCA achieves both lower pricing errors and higher SRs than PCA. However, as discussed later, this gain is smaller when moving out of sample.

[20] Using RP-PCA, we obtain an SDF that consists only of factors with significant means. This resembles the robust SDF of Kozak et al. (2020), KNS henceforth. However, KNS extract factors using PCA and then impose sparsity, by dropping factors with means below a threshold. Moreover, factors' SDF-weights shrink toward zero relative to the mean-variance weights. Thus, both the factors and their weights differ from ours, as RP-PCA changes the construction of the factors and relies on the mean-variance weights (Lettau and Pelger, 2020b). What is common between the two, however, is that both methods "overweight" the information in the first moments.

plausible choice. Moreover, RP-PCA appears to change materially the information spanned by the factors relative to PCA, in a way that the estimated factors should be more efficiently estimated and closer to the 'true' pricing factors, which complements the evidence uncovered by LP for equity portfolios. We test the robustness of these results along several dimensions, including the RP-weight, the SDF dimension, and out-of-sample analysis in Section 4.4. Next, we assign an economic interpretation to the latent factors.

Risk Exposures (ψ) and Factors Interpretation. Thus far, we extracted the latent factors and determined the structure of the currency SDF. Hence, we are ready to implement the three-pass method of GX. However, note that the estimates of the risk exposures and of the latent factors' prices of risk – the first-two steps of the GX method – are already subsumed into the RP-PCA factor estimation. On the one hand, the risk exposures, i.e., the currency portfolios' loadings on the latent factors, are implicit in Eq. (8). On the other hand, the point estimates of the latent factors' prices of risk are simply given by the factors' mean returns. This differs from GX as in their case factors are demeaned, and hence their risk prices are inherently model dependent and need to be estimated using the second pass of the FMB procedure. Next, we assess the portfolios' risk exposures and factor-by-factor explained variations, and in doing so relate the factors to the investment strategies.[21]

To begin with, we find that portfolios' exposures to the first factor, $\hat{F}_{1t}$, are positive and display a relatively small spread across portfolios. This evidence is consistent with the interpretation that $\hat{F}_{1t}$ is a strong factor that plays primarily the role of a level factor, similar to the tradable Dollar factor (e.g., Lustig et al., 2011; Verdelhan, 2018). However, we know from earlier results that the first latent factor has a non-trivial Sharpe ratio of 0.36 and enters the SDF, albeit with a small weight. This makes sense also in light of the fact that the tradable Dollar factor in our sample has a statistically significant average return (risk premium) at the 5 percent level, although it is economically small (2.62 per annum, with a t-statistic of 2.15). Its Sharpe ratio is 0.37, which is small in comparison with those of the most profitable currency investment strategies, and very close to the Sharpe ratio of $\hat{F}_{1t}$. While the literature consistently shows that the Dollar factor has a small risk premium and Sharpe ratio (e.g. Lustig et al., 2011), it is sometimes statistically significantly different from zero, depending on the cross section of currencies (i.e., using just developed or also emerging market countries) and the time period used.[22]

[21]As explained before, we center the empirical analysis around the orthogonalized latent factors. By doing this, we can also easily determine the distinct contribution of each factor in explaining portfolio returns.

[22]Figure A3 in the Internet Appendix reports the cumulative returns for the Dollar factor (Panel A) and the associated t-statistics calculated starting from a two-year window and expanding it in a recursive fashion (Panel B) for three samples of currencies: the 15 developed currencies sample and the 37 currencies sample used by Lustig et al. (2011), and our larger sample of 49 currencies. This allows us to inspect how the Dollar excess return and associated statistical significance vary with the size of the currency universe and over time.

Figure 3 presents the exposures (left panel) and explained variations (right panel) of the HML portfolios of the nine investment strategies to the estimated orthogonalized factors. To present the main findings, we focus on the HML portfolios as they are arguably more interesting than individual portfolios. Moreover, in this way, we can visualize the evidence for all strategies in a clear and concise manner.[23]

The second latent factor, $\hat{F}_{2t}$, retains a clear interpretation as it mostly relates to Carry. In fact, the Carry spread portfolio displays a strong positive exposure to $\hat{F}_{2t}$, and the associated R^2 is roughly 70 percent. Moreover, Carry portfolios' exposures to this factor increase monotonically, as we move from P1 to P5. All other HML portfolios are, to some extent, positively exposed to $\hat{F}_{2t}$. In terms of R^2s, $\hat{F}_{2t}$ mostly explains LYld, Term, LDC, and NFA spread portfolios, while it is substantially less relevant for Momentum, Value, and GAP strategies.

Conversely, $\hat{F}_{3t}$ is tightly linked to momentum investment strategies, and especially to ST Mom. In fact, ST Mom portfolios' loadings on $\hat{F}_{3t}$ increase from large negative (P1) to positive (P5) values, and the pattern across portfolios is almost monotonic. Similarly, LT Mom corner portfolios load with opposite signs on $\hat{F}_{3t}$. The GAP spread portfolio is also positively exposed to $\hat{F}_{3t}$. Notably, GAP portfolios' exposures to $\hat{F}_{3t}$ strongly resemble those of LT Mom portfolios. Hence, we uncover a novel relation between momentum strategies and a macro strategy such as GAP.

We can therefore conclude that the optimal currency SDF consists of at least a "Dollar" factor, a "Carry" factor, and a "Momentum" factor. Interestingly, while all strategies' spread portfolios are positively exposed to the first two latent factors, most strategies are negatively exposed to the "Momentum" factor. Thus, in line with Lustig et al. (2011) and many other papers, we include the "Dollar" and "Carry" factors in the currency SDF. However, our evidence shows that an additional "Momentum" factor should also feature in the SDF. Next, we turn to analyze the remaining factors.

The results make clear that the Dollar average excess returns display larger t-statistics as one expands the currency universe (the Sharpe ratio increases from 0.20 with 15 currencies to 0.26 with 37 currencies, and to 0.37 with 49 currencies). Furthermore, it is instructive to note that over some time periods even smaller cross sections of currencies would deliver a statistically significant risk premium at the five percent level (i.e., not only for 49 currencies but also for smaller currency universes). In short, the Dollar factor has an economically small risk premium which becomes more statistically significant (more precisely estimated) as one increases the universe of currencies used in its construction.

[23] Given that the HML portfolios are not included in the sample of test assets, their risk exposures are derived ex-post from the corner portfolio exposures of the nine investment strategies. Meanwhile, we evaluate the six factors' individual contributions to the nine HML portfolios' explained variations using Eq. (7). Specifically, we estimate 9×6 OLS time-series regressions (i.e., six regressions for each of the nine HML portfolios), as we add factors one by one; hence, we consider SDFs of increasing dimension. In the Internet Appendix, Figures A1 and A2 present, respectively, the individual portfolios exposures ($\hat{\psi}_n$) and explained variations (R_n^2) by latent factor. We omit to plot portfolios' exposures and explained variations associated with the first factor, as it becomes easier to visually detect the exposures and marginal contributions of the other factors.

Of particular interest is $\hat{F}_{4t}$, given that it also displays a positive risk premium, and its inclusion in the SDF increases somewhat the maximal SR and reduces the pricing errors. Moreover, it has an intuitively clear interpretation of "long Value short (long-term) Momentum" factor, or simply "Value" factor. In fact, it presents a close nexus with the Value spread portfolio. P1 and P5 Value portfolios display negative and positive loadings on $\hat{F}_{4t}$, respectively. The loadings of the middle portfolios reveal a monotonically increasing pattern. Meanwhile, it is also apparent the strong association between $\hat{F}_{4t}$ and the LT Mom spread portfolio. However, LT Mom portfolios display monotonic but decreasing exposures to $\hat{F}_{4t}$. Therefore, $\hat{F}_{4t}$ could partly be responsible for the negative correlation between (long-term) momentum and value strategies documented in Table A4 and by Asness et al. (2013) for many other asset classes.[24]

Latent Factor Prices of Risk (γ). As a first cross-validation exercise, we check that the model-free estimates of the latent factors' prices of risk (i.e., the factor means) match those obtained using the second-pass of the GX method, i.e., the FMB estimates. We find that the two point estimates are equal (i.e., $\hat{\mu}_F = \hat{\gamma}$), which is reassuring as it shows that the no-arbitrage assumption is preserved (e.g., Cochrane, 2005). Specifically, for the selected SDF with $\omega = 20$, the means (or prices of risk) of the pricing factors are $\hat{\mu}_{F,1}$= 18.7, $\hat{\mu}_{F,2}$= 11.3, and $\hat{\mu}_{F,3}$= 9.2 percent per annum. Based on Newey-West standard errors, $\hat{\mu}_{F,1}$ is statistically significant at the five percent level, while the remaining two at the one percent level (see Table A8). The estimates of the prices of risk of the latent factors are not particularly informative per se, but they are a crucial input in the estimation of the risk premiums of the nontradable factors, λ_gs. To obtain a robust estimate of λ_g, it is important that the latent-factor model does a good job in pricing the test assets. Only if this is the case, one can argue that the price of risk estimates of the candidate factors are not affected by omitted-variable and measurement-error problems.

Test Assets' Pricing Errors. The superior pricing performance of the RP-PCA model with $\omega = 20$ relative to the PCA model emerges clearly from Table 1. To better appreciate the differences between these two estimation methods, Figure 4 plots realized versus model-implied average portfolios' excess returns. If a model prices perfectly the cross section of portfolio returns, all data points lie on the 45 degree line. We find that the pricing performance of the RP-PCA model based on the optimal three-factor SDF is very accurate: the pricing errors are indeed small, and there is no tendency for the model to systematically misprice portfolio returns. By inspecting the two-factor SDF evidence, the gain from adding

[24] The $\hat{F}_{5t}$ and $\hat{F}_{6t}$ risk exposures, albeit relevant for some specific portfolios, display no clear patterns. Thus, it is hard to assign a precise interpretation. This is not surprising exactly because they are weak time-series factors.

an extra factor clearly emerges. This reiterates the importance of including the "Momentum" latent factor to the currency SDF, in addition to the "Dollar" and "Carry" latent factors. However, for a factor model to reflect the 'true' SDF, all cross-sectional pricing errors should be zero on average.

A natural way to proceed would be to perform standard tests of the null hypothesis that the alphas are jointly zero. However, these types of tests – such as for example the Gibbons-Ross-Shanken (GRS) test – are based on the assumption that N is constant and $T \to \infty$, while the RP-PCA estimator is derived under the assumption that both $N, T \to \infty$. This implies that the covariance matrix no longer converges to the population matrix, and the tests are biased even in large samples (e.g., see Lettau and Pelger, 2020b). While some papers propose remedies to obtain consistent estimates of the covariance matrix (see Giglio et al., 2021a for a detailed review), and hence address some of the drawbacks of the GRS test, we opt for a simple multiple-testing approach. Our reasoning is as follows: the RP-PCA estimator assumes a factor model with zero alpha, so that each asset should have zero average pricing errors in Eq. (1), and as a result the model would span the entire asset space. Hence, we perform $N = 46$ tests of the null hypothesis $\mathcal{H}0$: $\bar{\epsilon}_n = 0$ for $n = 1, \ldots, N$, and assess how many assets have significant average pricing errors at the 5 percent significance level, as we vary the dimension of the SDF. The results are clear-cut. Using a two-factor model we reject the null hypothesis in 14 cases (e.g., including the ST Mom corner portfolios), while only one test asset (Value-P5) has a statistically significant average pricing error using the three-factor model. With the four-factor model, none of the assets has significant average pricing errors. In short, a four-factor model ensures that the average pricing errors are zero for all test assets, although we would argue that the three-factor model possibly achieves the same outcome.[25]

A related question is whether the first latent factor is required in the SDF as we know that it is a strong factor on which test-asset returns load with similar positive exposures (small cross-sectional spread in asset exposures). Indeed, the first latent factor is relevant mainly because it captures the time-series variation in the test-asset returns. Therefore, we carry out the same sequence of tests omitting the first latent factor. The outcome of this exercise is that the number of statistically significant average pricing errors increases sharply when the first latent factor is omitted: 24 when using only the second latent factor, 11 when using a model with only the second and third latent factors, and 7 when using the second, third and fourth latent factors. This is consistent with our earlier interpretation

[25]Recalling that the three-factor model only produces one significant average pricing error (with a p-value of 0.035) out of 46 assets, this can clearly arise just by chance (false discovery). For example, using a Bonferroni correction, none of the p-values is smaller than the Bonferroni corrected p-value ($0.05/N = 0.0011$), although this is known to be a conservative approach (e.g., Giglio et al., 2021b).

that the first latent factor enters the optimal SDF and, although it has a smaller Sharpe ratio relative to the second and third latent factors, it plays a non-negligible role in the pricing of our test-asset returns.

Finally, the comparison between left and right panels of Figure 4 highlights the lower pricing performance of the PCA models. This is evident if one compares models' with SDFs of equal size and, even more, if one contrasts the evidence for the respective optimal SDFs selected by the statistical tests (i.e., two- and three-factor SDFs for PCA and RP-PCA, respectively). Overall, this analysis validates the use of $\varphi(F_{1-3})$ based on RP-PCA to determine the prices of risk of the candidate factors.

On the Relationship between Latent and Tradable Factors. We showed earlier that the first latent factor is most closely related to the tradable Dollar factor, the second latent factor to the currency Carry factor, the third latent factor to the short-term currency Momentum factor, and the fourth latent factor to the currency Value factor. We now report evidence on the relationship between the latent factors and the tradable factors using regression analysis to establish the strength of this relationship more formally. This analysis will show that the two types of factors are not identical and, hence, cannot be used interchangeably (e.g., the second latent factor cannot be replaced by the tradable Carry factor).

In Panel A of Table A9, we report results from running separate univariate regressions of each of the first, second, third and fourth latent factors (extracted using the benchmark case of RP-PCA with a penalty weight equal to 20) on the tradable Dollar, Carry, short-term Momentum and Value factors, respectively. If the latent factors are identical to the tradable factors, one should expect to observe: (i) the intercept (or alpha of the latent factor) is zero, (ii) the slope coefficient is one, and (iii) the R^2 is close to one. We do not find (i), (ii) and (iii) holding simultaneously in any of the four regressions. Specifically, in each regression, the slope coefficient is positive and strongly statistically significant, but only in one case it is close to one ("Carry"). The intercept is statistically insignificantly different from zero for two of the four regressions ("Dollar" and "Value"). The R^2s of the four regressions are 0.99, 0.70, 0.47, and 0.57. The highest R^2 occurs for the regression of the first latent factor on the Dollar factor, where recall that the alpha is statistically insignificant, essentially showing that the first latent factor can be interpreted as a leveraged Dollar factor (the slope coefficient is above seven). The other three latent factors clearly contain somewhat different information from the tradable factors to which they are most closely related. In essence, the latent factors in the SDF resemble the Dollar, Carry, Momentum, and Value tradable factors, but they are not identical to them.

These results have a clear interpretation, as they imply that the optimal SDF with latent factors cannot be replicated by using tradable factors. Notably, even the four tradable factors taken together cannot fully explain the second and third latent factors in time-series regressions in that statistically significant alphas remain (see Panel B of Table A9). Thus, in the sense of Barillas and Shanken (2017) these latent factors are not subsumed by the above four observable tradable factors. A factor model that uses ten observable factors (one for each of the underlying strategies in our test assets in addition to the Dollar factor) can explain well our latent factors with high R^2, but even then an economically small but statistically significant alpha remains for the third latent factor (Panel C of Table A9). This means that the latent factors capture information that goes beyond the tradable factors for Dollar, Carry, Momentum and Value, and this is key for the latent-factor SDF to price not only the returns from these four investment strategies, but also the returns from other currency strategies that rely on different sorting variables (such as global imbalances, output gaps, etc.) considered in our paper. Put simply, while the four latent factors fully span the cross section of test assets, this is not the case for the four tradable factors.[26] It should therefore be clear that the optimal latent-factor SDF cannot be replaced by a parsimonious factor model that uses a small set of canonical tradable currency factors.

4.3 Candidate Factor Risk Premia

`Spanning Regressions.` The last pass of the GX procedure consists of projecting each of the candidate nontradable factors onto the space spanned by the estimated latent factors. We do this by estimating the following regressions

$$g^{\iota}_{jt} = a_{jk} + \hat{F}_{1:kt}\eta^{\top} + u_{jkt}, \quad j = 1, \ldots, J, \quad k = 1, \ldots, K, \quad t = 1, \ldots, T, \tag{15}$$

where g^{ι}_{jt} is the AR(1) innovation of the selected j-th nontradable factor. We again perform the regression analysis by expanding the set of latent factors, by adding one factor at a time, $\hat{F}_{1:kt}$, to single out their marginal contributions in terms of R^2s. We therefore run a total of $J \times K$ time-series regressions. GX show that the R^2s help quantify the measurement errors in the nontradable factors. Specifically, a low (high) R^2 implies a big (small) measurement error.[27]

[26] Indeed, we find that we cannot price the cross section of test assets using an SDF consisting of the Dollar, Carry, Momentum and Value tradable factors. In fact, using this observable four-factor model and based on the GRS test statistic, we strongly reject the null that the alphas are jointly zero.

[27] Eq. (15) is the empirical counterpart to Eq. (10). It differs as we include the intercept and do not use the factors in deviation from their means. In this way, the R^2s are more meaningful, and yet the η-exposure estimates are unchanged. While the difference is negligible, when we compute the standard errors of the candidate factors' prices of risk using the formula in GX, we implement Eq. (10). Also note that, after having computed the factors' AR(1) innovations, we then standardize them such that the resulting factors

`Explained Variation` (R^2)`.` Figure 5 shows the R^2s associated with each of the three latent pricing factors, grouped by type of candidate factor (we present the evidence using all six latent factors in Figure A4 in the Internet Appendix). Within each group, candidate factors are sorted by the total R^2s. We find that the measurement-error problem is pervasive, as the R^2s are generally low. At the same time, some distinct patterns across types of candidate factors emerge. A few financial factors display R^2s that exceed 10 percent; these factors mostly relate to financial and liquidity conditions, volatilities, and intermediaries' leverage. For most of these factors, the overall R^2s are driven by all three factors, albeit mainly by the second factor (i.e., the "Carry" latent factor). There are of course a few exceptions as is clearly the case for the global financial condition index. (Its R^2 is above 35 percent, and is mostly driven by $\hat{F}_1$, although the absolute contribution of $\hat{F}_2$ is also large.)

In comparison with financial factors, the R^2s of text-based factors are generally lower. Moreover, the "Carry" latent factor is by far the most relevant factor, given that for many factors (especially for those with higher R^2s) it accounts for almost the entire R^2s. The U.S. EMV factors' R^2s tend to be higher than those associated with the U.S. EPU indices, with the exception of the global EPU index. Finally, turning to macro factors, they present much lower R^2s, typically in the range of 1-2 percent. The overall picture of the drivers is more mixed. In fact, for a number of macro factors, the "Dollar" and "Momentum" latent factors are the main determinants of the R^2s.

`Factor Exposures` (η)`.` Before inspecting the estimates of the η-exposures, we note that all latent pricing factors are procyclical factors, as they command positive risk premiums. In essence, procyclical factors rise in good states of the world, while dropping in bad states. It follows that a candidate factor with a positive (negative) η-exposure to a specific risk factor is procyclical (countercyclical) with respect to that source of risk. Thus, the η-exposures are economically meaningful objects. However, it is important to note that a candidate factor can present exposures of opposite signs to the individual pricing factors. Therefore, only the risk premium of the candidate factor will reveal whether the factor is either procyclical (positive risk premium), countercyclical (negative risk premium), or acyclical (zero risk premium) with respect to the state of the world.

Table 2 reports the estimates of the η-exposures of the factors. In the table, to help summarize the evidence, we focus on the candidate factors with significant prices of risk, based on the optimal SDF (we provide the evidence for all candidate factors in the Internet Appendix, Table A10). To start with, we note that financial factors tend to have exposures of the same sign to the "Dollar" and "Carry" latent factors. The signs of the η_2 estimates are consistent with the usual sources of risk inherent in currency carry strategies (e.g., liquidity

have also unit variances, which helps compare the estimates across candidate factors.

and volatility risks) previously documented by the literature; however some specific risk factors are novel (e.g., otic, move). Interestingly, the exposures to the "Momentum" latent factor generally take opposite sign, but a smaller number of these exposures are statistically significant. Put differently, this evidence suggests that carry and momentum strategies respond to some of the same financial risk factors, but in opposite directions. Turning to the text-based factors, the evidence is even more clear-cut: none of the factors is exposed to the "Dollar" factor, while all factors are negatively exposed to "Carry". These factors' exposures to "Momentum" again take opposite sign with respect to "Carry", but are much smaller in absolute size, and are statistically significant only in a few cases (see Table A10).

Overall, we uncover a tight nexus between FX and other markets that is mainly channeled through the "Carry" factor, lending support to the argument of Koijen et al. (2018, p. 198) that "... [carry] could be a unifying concept that ties together many return predictors disjointly scattered across the literature from many asset classes." Finally, as expected, macro factors display only few significant η-exposures.

`Return-Based Factors` ($F\eta^\top$)**.** To complement the above analysis, we visually inspect some examples of return-based factors. A return-based candidate factor is the original factor converted into a return factor using the η-exposures, being a linear combination of the latent factors ($\hat{F}\hat{\eta}^\top$). In practice, the original nontradable factor becomes a return-based factor that loads on the underlying currency portfolios.

Figure 6 shows selected candidate factors, transformed into return-based factors using SDFs including up to three factors. In this way, we can appreciate how the return-based factors' evolutions and levels change as the "Momentum" factor is added to the SDF. Top panels present two examples of factors (gepu and gvol) that are exposed significantly to the "Carry" factor, but not to "Momentum". Conversely, bottom panels refer to factors (icap and gliq) that are exposed significantly to both "Carry" and "Momentum" factors (Table A10), but with opposite and economically large estimates. It is evident that, for icap and gliq, by moving from the two-factor to the three-factor SDF the factor mean returns drop significantly in absolute terms, and for gliq the risk premium eventually vanishes. The in-depth analysis of the factors' risk premiums is presented next.

Risk Premia. In what follows, we present the last piece of evidence resulting from the third pass of GX. That is, we report the estimates of the risk premiums of the nontradable candidate factors, free from both the omitted-variable and measurement-error problems. As explained in Section 2 (and shown in Section 5 in simulation), one can also use the standard FMB two-pass procedure to obtain such estimates but, crucially, only if all relevant control factors are included in the SDF, and factors are measured without noise. The evidence reported so far clearly shows that the measurement-error problem is material. The omitted-variable problem is also likely to be important, and can therefore add to the measurement-error problem. To shed light on the severity of both problems, we first estimate factor risk premiums by means of the standard FMB two-pass method.

`FMB Two-Pass Method.` We rely on univariate SDFs, which consist of a constant and the candidate factor at hand. Hence, for each candidate factor g_{jt}, we specify the SDF as $\varphi_t = 1 - g_{jt}^{\iota} b_j$. We intentionally omit from φ_t other potentially relevant risk factors, f_t, that could enter the SDF along with the candidate factor, g_t. In this way, the omitted-variable bias can manifest in its full strength. We find that over 90 out of the 134 candidate factors present estimates of the prices of risk that are statistically significant at least at the 10 percent level (of which more than half are macro factors). Thus, the FMB estimates seem to point to a very large number of significant factors, i.e., a "factor zoo", for FX returns.

`GX Three-Pass Method.` Table 3 presents the factor risk-premium estimates obtained using the augmented three-pass method implemented with baseline RP-weight, $\omega = 20$. Along with the risk-premium estimates (λ_g), and the associated standard errors (se), the table reports the candidate factors' Sharpe ratios, to better evaluate their economic relevance. It also presents the p-value for the Wald test that the candidate factor is weak (pval), where the null hypothesis is that the factor is weak, i.e., $\eta = 0$. We refer to Giglio and Xiu (2021) for details on the computation of risk-premium standard errors and the weak-factor test p-value.

Before turning to the individual factor estimates, we note that the three-pass absolute risk-premium estimates are substantially lower than the FMB ones. In Table 3, this finding holds to a large extent regardless of the specific SDF considered. Too high estimates of the prices of risk are likely to be caused especially by the measurement-error problem. In fact, when a factor is measured with noise, an attenuation bias characterizes the estimates of the portfolios' risk exposures to that factor in the first pass of FMB. This bias in turn leads to inflated prices of risk estimates in the second pass (e.g., Adrian et al., 2014). A close look at the table suggests that the problem seems to be less relevant for financial than for text-based and macro factors.

Based on the optimal SDF, $\varphi(F_{1-3})$, we find that 43 out of the 134 candidate factors have statistically significant risk premiums, which is a much shorter list than that uncovered using FMB. Among these, we find that the financial factors with significant risk premiums are 12 out of 24. The global volatility factor (gvol) of Menkhoff et al. (2012a) stands out, as its risk premium is large and precisely estimated. Results are similar, albeit weaker (statistically significant only at the 10 percent level), for the global equity volatility factor (geqrv) of Lustig et al. (2011). The systematic FX liquidity measure (sliq) of Karnaukh et al. (2015) also carries a statistically significant risk premium, while the global liquidity measure (gliq) of Menkhoff et al. (2012a) does not. Moreover, a number of factors relating to liquidity (noise and psliq) and volatility (move, vxo, and eqrv) conditions in the U.S. bond and equity markets turn out to have statistically significant risk premiums. These factors highlight the tight link between FX returns and other markets. Interestingly, the quantity-based TIC flow measure (otic), proxying for foreign central banks' demand for US Treasuries, is positive and significant. Thus, it is a procyclical factor, possibly suggesting that foreign central banks tend to build up their reserves in good states of the world. Global financial conditions (gfc) also seem to matter for FX returns.

Turning to the text-based factors, 14 out of 30 have statistically significant risk premiums. In comparison with financial factors, the number of significant text-based factors drops even more substantially relative to FMB. The global EPU index of Baker et al. (2016) stands out as its risk premium is the highest (in absolute terms) and the most precisely estimated. Conversely, the U.S. EPU indices are not priced. At the same time, several EMV indicators display statistically significant negative risk premiums. Some of the category-specific EMV trackers are even more precisely estimated than the overall index; namely, those relating to the macroeconomy and monetary policy (i.e., emv mout, emv mqnt, and emv mp).

To conclude the list of factors, we find that only a few macro variables are (weakly) priced in the cross section of currency returns; specifically, 17 out of 80 macro factors, stemming from six distinct macro factors measured at different frequencies. In particular, the world unemployment growth rate specified in differences versus the U.S. (unew/us) displays a negative risk premium, at many frequencies. The world industrial production factor also presents a statistically significant negative risk premium, especially when specified in differences versus the U.S. (ipw/us) at the quarterly frequency. The risk premium of world inflation (cpiw) is also negative. Consumption growth risk is negative and weakly significant (cus). However, unlike the other types of factors, several of the signs of the macro risk premiums seem not to align with theoretical priors (e.g., Lustig and Verdelhan, 2007; Zviadadze, 2017).[28]

The absolute magnitude of macro risk premiums is lower, on average, than that of text-based and financial factors with significant risk premiums. Conversely, macro factors' SRs tend to be higher, especially those associated with unemployment. However, it is also evident that most of the macro factors are weak factors, according to the GX test (*pval*).

[28]For example, considering the prospective of the U.S. investor, consumption growth risk is high in good states of the world and low in bad states. As a result, it should command a positive premium, while it turns out to be negative.

Finally, Figure A5, in the Internet Appendix, shows the relative contribution of each of the four latent factors to the candidate factor risk-premium estimates. In essence, it shows an accounting decomposition of the risk premiums to illustrate, on average, the contribution of each latent factor in the SDF to the determination of the nontradable factors' risk premiums. The key takeaway is that, on average across all candidate factors, the contribution of the first latent factor to pricing the cross-section is economically small – on average, only about 9 percent of the risk premiums estimated across our full set of candidate factors displayed in Table 3 is accounted for by the first latent factor. Indeed, over 80 percent is accounted for by the second and third latent factors taken together.

4.4 Robustness, Stability and Weak Factor Analyses

`Robustness Analysis.` To complete the baseline analysis, we perform a number of robustness checks, which are presented in detail in the Internet Appendix (Section V.1). The main results can be summarized as follows. First, we show that selecting the optimal SDF is key to obtain precise estimates of nontradable factors' currency risk premiums. In particular, the omission of relevant pricing factors (i.e., $\hat{F}_3$) is far more harmful than the addition of less relevant ones (i.e., $\hat{F}_4$). Second, the choice among reasonably high values of the RP-weight leads to small differences in the risk-premium estimates. Third, by including the HML portfolios to the panel of currency portfolios, some of the estimated latent factors better explain some of the high risk-premium currency strategies (e.g., GAP), but this information does not affect much the structure of the SDF, so that the method essentially selects the same relevant candidate risk factors as in the baseline results. Fourth, we re-estimate the three-pass model by allowing for an unrestricted zero-beta rate (ZBR) and find that the risk-premium estimates are robust.[29]

`Stability Analysis.` We then assess the stability of the SDF in both out-of-sample and in-sample time-varying settings, and provide some time-varying candidate factor risk-premium estimates (Section V.2). The in-sample results are largely confirmed out of sample. However, the performance of RP-PCA deteriorates out of sample, while PCA displays higher degree of stability. Therefore, there seems to be still a sizable gain in choosing RP-PCA over PCA, but this gain shrinks out of sample. Moreover, the out-of-sample evidence suggests more clearly a model with three factors, as the contribution of the fourth factor to the maximal Sharpe ratio is essentially nil. The factor structure appears rather stable over

[29] Specifically, we allow for a constant in the second and third steps of the RP-PCA three-pass estimator (i.e., Eqs. (9) and (10)). We find that the estimate of the ZBR is essentially nil for multifactor models of any dimension, and hence the candidate factor risk-premium estimates are virtually unaffected by allowing for the ZBR. To show this, we focus on the tradable factors as we can benchmark their risk-premium estimates to their excess-return sample means (see Section V.1 in the Internet Appendix).

time, as indicated for example by the fact that the GX and O tests consistently point to a three-factor model throughout our recursive analysis (based on an initial window of ten years). Also, the candidate factors' risk-premium estimates do not show significant degrees of time variation, as long as the estimation window is sufficiently long, and the SDF includes at least the first three latent factors. Therefore, the unconditional three-pass model, if well specified, provides a satisfactory description of dynamically rebalanced FX portfolio returns.

`Weak Candidate Factor Analysis.` The three-pass procedure of GX tackles both the omitted-variable and measurement-error problems in the estimation of factor risk premiums. However, the method as such – regardless of whether factors are extracted via PCA or RP-PCA – is not designed to explicitly address the issue of weak candidate factors. The weak-factor problem manifests if only a subset of the test assets is exposed to the candidate factor, and this can in turn disrupt the inference on the candidate factor's risk premium. In light of these considerations, we also assess the robustness of the candidate factors risk-premium estimates using the supervised principal component analysis (SPCA) recently proposed by Giglio et al. (2021c). This novel method is designed to explicitly tackle the omitted-variable and measurement-error problems also accounting for the possibility that the candidate factor of interest is *weak*. We carry out the fully-fledged SPCA in the Internet Appendix (Section V.3). Below, we present the main findings.

To start with, we find that the nontradable factor risk-premium estimates are largely robust to the estimation method used. In fact, the estimates obtained with SPCA are consistent with our baseline three-pass estimates. Above all, this additional analysis confirms the disconnect between macro variables and currency portfolios. We can now also exclude that the disconnect is imputable to a weak-factor problem. Moreover, the cross-validation exercise allows us to further filter out factors that cannot be hedged out of sample by the currency assets, shrinking further the list of relevant candidate factors. We have seen how, starting from 134 factors, the number of statistically significant risk premiums reduces from over 90 using the FMB procedure to 43 using the three pass-method. This is due to allowing for omitted-variable and measurement-error biases. Using SPCA, where we further require a positive cross-validation out-of-sample R^2, the number of factors with significant risk premiums further drops to 18, which is only 13 percent of the initial list of 134 factors.[30]

[30] It is conceivable that allowing also for multiple-hypothesis testing bias would further reduce this number. The role of this kind of bias in the context of the three-pass procedure and SPCA requires further study, along the lines of Harvey et al. (2016) and Giglio et al. (2021b), which we leave for future research.

5 Simulation Analysis

In this section, we study the finite-sample performance of the three-pass inference using Monte Carlo simulations. We essentially tackle two key questions. First, is the three-pass method *reliable* in finite samples, with N and T equal to the dimension of our FX portfolio returns? Second, are the omitted-variable and measurement-error problems relevant for pricing currency portfolio returns, and hence is the method *desirable* for pricing currency risks?

Next we briefly describe the simulation exercise, and summarize the main findings. We present the fully-fledged simulation results in the Internet Appendix (Section VI).

`Simulation Method`. We set up the simulation exercise following closely GX, with the only relevant methodological difference due to the use of RP-PCA to extract the latent factors that drive the data generating process (DGP). Moreover, we tailor the calibration to the specific features of the FX market. This is important because, although GX show a good performance of the three-pass estimator in simulation also for combinations of N and T that resemble the one used in our study, it is not obvious that the estimator performs the same in our case. The factor structures driving equity and FX portfolio returns may well differ, and this can in turn weigh on the estimator performance.[31] Specifically, in the simulations we consider a four-factor DGP consisting of the de-noised Dollar, Carry, ST Mom, and Value currency factors. To remove the noise from the observed z-factors, we use the three-pass estimator with four latent factors ($k = 4$), extracted using RP-PCA with baseline RP-weight ($\omega = 20$).

By doing so, the four de-noised z-factors should span the entire SDF (as we know from Section 4.2 that four latent factors do so and generate zero average pricing errors for all 46 assets), and hence the simulated asset returns should mirror the properties of the observed ones. This is crucial to recover the *true* factor risk premiums via the three-pass estimator.

Next, as in GX, we assume that we do not observe the true four factors but only noisy versions of them, plus a potentially spurious noisy candidate nontradable factor. To begin with, we calibrate the candidate factor to U.S. industrial production (ipus), which according to our three-pass estimates qualifies as a spurious factor also for FX returns. However, we

[31] In fact, the cross section of FX test assets is relatively small, and the underlying data are driven by fewer factors, compared to the case of equities, studied for example by GX. At least until recently, the benchmark model for FX returns has been the two-factor model of Lustig et al. (2011), consisting of a Dollar and a Carry factor. Our analysis, however, suggests that with a reasonably large N (at least much larger than the small cross sections typically used so far in the FX literature), a two-factor SDF is likely to omit relevant sources of FX risk, and that at least three and potentially four latent factors are required to achieve full spanning of the entire SDF and robust estimates of risk premiums. Therefore, in larger cross sections, not only the measurement-error problem, but also the omitted-variable problem is likely to be relevant for FX returns.

then repeat the analysis replacing ipus with either gvol or icap (the global volatility of Menkhoff et al., 2012a, and the intermediaries' capital ratio of He et al., 2017, respectively). These two financial factors are of particular interest as they exemplify non-spurious factors whose risk premiums estimates are affected to different extents by the dimension of the latent-factor SDF considered (as is evident already from Section 4.3). Taken together, these candidate factors capture the properties of the nontradable factors considered in the empirical analysis, and hence we consider gvol, icap, and ipus as nontradable candidate factors in our simulation.

We calibrate the parameters that drive the DGP to exactly match their counterparts in the data (Panels A-C, Table 4). We then simulate from the DGP, by generating $M = 10,000$ artificial Monte Carlo realizations of asset returns with $N = 46$ and $T = 410$, and of the noisy nontradable factors.

`Simulation Results`. To begin with, we assess the accuracy of the simulated asset returns by comparing the moments of the observed returns with the moments of the simulated returns (Figure 7).

Having established the accuracy of the simulations, we can now turn to evaluate the performance of the three-pass estimator on the simulated data. We assess the models' ability to recover the *true* risk premiums, asymptotic standard errors, and Sharpe ratios of the tradable and nontradable factors (displayed in Panel D, Table 4), which are the key outputs of the three-pass procedure (presented earlier in Table 3). We do so by applying the three-pass method with baseline RP-weight to the simulated data (whereby factors and test assets are simulated with noise), using SDFs of expanding dimension. To complete the analysis we also evaluate the performance of the two-pass estimator, by considering SDFs with different numbers of omitted factors and with factors measured with or without noise. Taken together, this analysis allows us to assess the finite-sample performance of the three-pass estimator and hence its reliability, but also shed light on the relevance of the issues of omitted factors and measurement error in the factors driving FX returns when using the conventional two-pass estimator.

`Three-Pass Estimator`. The three-pass estimates of the candidate factor risk premiums establish two important results. First, the augmented three-pass estimator delivers an accurate recovery of the tradable and nontradable factor *true* risk premiums, standard errors, and Sharpe ratios in simulation (see Table 5). Second, the GX central-limit result holds, confirming that the three-pass estimator is highly reliable also in finite samples that match the properties of our FX portfolio returns – full details are in the Internet Appendix (Figures A17–A23). Moreover, we note that the recovery of the true risk premiums shows the rotation-invariance result in our setting. This is because the DGP is driven by the denoised z-factors, but the risk premiums are estimated via the three-pass method and, hence, as linear combinations of the latent-factor risk premiums. Furthermore, we find that for most factors we can recover the true risk premiums even using parsimonious factor models (especially for higher RP-weights), but for some factors it is beneficial to use models that include more latent factors. Using five-factor models (thus an additional factor than in the true model), we can verify the central-limit results for all candidate factors.

`Two-Pass Estimator`. The two-pass estimator analysis on simulated data shows that the omitted-variable problem can be material, leading to distorted risk-premium estimates. In short, the two-pass estimator recovers the true premiums only if the SDF is correctly specified, i.e., if the true control factors are known to the researcher. In some cases, even if none of the relevant factors are omitted from the SDF, and yet some of the factors are measured with noise, one cannot retrieve the true risk premiums of all factors. Therefore, unlike for the three-pass estimator, both the omitted-variable and measurement-error problems manifest clearly in simulation with the two-pass estimator – full details are in the Internet Appendix (Table A25, and Figures A24-A26).

Overall, the simulation results demonstrate the good performance of the three-pass estimator, as long as the model includes enough latent factors, also in a currency setting. Moreover, they lend support to the argument made in Section 2: that is, omitting relevant pricing factors from the currency SDF, and/or measuring the factors with noise, can severely distort the two-pass risk-premium estimates. Put simply, the three-pass estimator appears to be both *reliable* and *desirable* for modeling FX portfolio returns, and hence represents a valuable method to unveil the sources of the risk-return trade-off in currency investment strategies.

6 Concluding Remarks

In this paper, we revisit the macro-financial sources of the risk-return trade-off inherent in currency investment strategies through the lenses of the three-pass method of Giglio and Xiu (2021), which we combine with the Risk-Premium PCA method of Lettau and Pelger (2020a,b). This approach allows us to shed light on the optimal currency SDF and to provide estimates of the risk premiums of a large number of nontradable factors, while allowing for both omitted-variable and measurement-error biases.

We find that, using RP-PCA to extract the latent factors, the optimal currency pricing kernel includes at least three latent factors: a strong U.S. "Dollar" factor, and two weak, high Sharpe ratio "Carry" and "Momentum" slope factors. The evidence for a fourth weak latent pricing factor, which relates to “Value”, is not clear-cut. We note that these latent factors are closely related but they are not identical to the observable U.S. Dollar, Carry, Momentum and Value tradable factors. Indeed, the optimal latent-factor pricing kernel cannot be replaced by a parsimonious reduced-form model based on these tradable factors, as the latent factors embed pricing-relevant information that goes beyond the tradable factors; this is key to price the full set of portfolios considered in our cross section of test assets. We show that the optimal three-factor pricing kernel delivers a reasonably high maximal Sharpe ratio and low pricing errors, while the explained systematic variation of the portfolios is comparable to PCA. At the same time, using standard PCA, the “Momentum” factor would be omitted from the pricing kernel, due to its low time-series “signal strength”.

Based on this optimal pricing kernel, we then show that a large portion of our long list of nontradable factors is due to noise. This helps explain why the standard two-pass FMB method can deliver inflated estimates of nontradable factor prices of risk. In particular, we find that this problem is pervasive for macro factors, while it is more contained for some financial and text-based factors. Moreover, we document that the “Carry” latent factor is the most relevant factor for financial and text-based factors. However, the omission of the “Momentum” latent factor can lead to severely distorted risk-premium estimates. In fact, many financial factors display significant exposures to both the “Carry” and “Momentum” latent factors, but of opposite signs. The “Dollar” factor provides a much smaller contribution to the risk premium estimates than “Carry” and “Momentum” latent factors.

Overall, we find that a small fraction of nontradable – mostly financial and text-based – factors have statistically significant risk premiums. Some of the nontradable factors previously uncovered by the literature turn out to be less or even not relevant, while other factors (i.e., which were not previously related to currency returns) appear to be relevant, disclosing a tight link between FX and other markets, mainly channeled through the “Carry” factor. In particular, the results highlight the relevance of several volatility (e.g., the global FX volatility factor of Menkhoff et al., 2012a) and uncertainty (e.g., the global EPU index of Baker et al., 2016) measures, and of some liquidity indicators. Conversely, the results confirm a substantial disconnect between currency returns and macro variables, especially as both sources of bias are accounted for. Such disconnect manifests even if we use estimators that account for the possibility that macro factors are weak factors in the FX cross section.

Taken together, the evidence uncovered contributes to our understanding of the risk-return trade-offs inherent in currency investment strategy returns. Moreover, the results highlight the empirical relevance of achieving robust risk-premium estimates, which takes central stage in the current asset pricing research agenda. In particular, we make some progress in taming the FX “factor zoo” which, albeit in its infancy compared to other markets, is rapidly expanding. Finally, the finding that the optimal currency SDF comprises at least three factors with different strengths and risk premiums could guide future theoretical research in international macro-finance with the ultimate objective of deriving currency models that rationalize such properties from first principles.

References

Adrian, T., E. Etula, and T. Muir (2014): "Financial Intermediaries and the Cross-Section of Asset Returns," *Journal of Finance*, 69, 2557–2596.

Akram, Q. F., D. Rime, and L. Sarno (2008): "Arbitrage in the Foreign Exchange Market: Turning on the Microscope," *Journal of International Economics*, 76, 237–253.

Ang, A. and J. Chen (2010): "Yield Curve Predictors of Foreign Exchange Returns," *Working Paper*.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013): "Value and Momentum Everywhere," *Journal of Finance*, 68, 929–985.

Bai, J. and S. Ng (2002): "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70, 191–221.

——— (2006): "Evaluating Latent and Observed Factors in Macroeconomics and Finance," *Journal of Econometrics*, 131, 507–537.

Baker, S. R., N. Bloom, and S. J. Davis (2016): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131, 1593–1636.

Baker, S. R., N. Bloom, S. J. Davis, and K. Kost (2019): "Policy News and Stock Market Volatility," *Working Paper*.

Bali, T. G., S. J. Brown, and Y. Tang (2017): "Is Economic Uncertainty Priced in the Cross-Section of Stock Returns?" *Journal of Financial Economics*, 126, 471–489.

Barillas, F. and J. Shanken (2017): "Which Alpha?" *The Review of Financial Studies*, 30, 1316–1338.

Bekaert, G. and R. Hodrick (1993): "On Biases in the Measurement of Foreign Exchange Risk Premiums," *Journal of International Money and Finance*, 12, 115–138.

Bekaert, G., M. Hoerova, and M. Lo Duca (2013): "Risk, Uncertainty and Monetary Policy," *Journal of Monetary Economics*, 60, 771–788.

Bekaert, G., M. Wei, and Y. Xing (2007): "Uncovered Interest Rate Parity and the Term Structure," *Journal of International Money and Finance*, 26, 1038–1069.

Benetrix, A., P. Lane, and J. C. Shambaugh (2015): "International Currency Exposures, Valuation Effects and the Global Financial Crisis," *Journal of International Economics*, 96, S98–S109.

Berg, K. and N. Mark (2018a): "Global Macro Risks in Currency Excess Returns," *Journal of Empirical Finance*, 45, 300–315.

——— (2018b): "Measures of Global Uncertainty and Carry-Trade Excess Returns," *Journal of International Money and Finance*, 88, 212–227.

Brogaard, J. and A. Detzel (2015): "The Asset-Pricing Implications of Government Economic Policy Uncertainty," *Management Science*, 61, 3–18.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2009): "Carry Trades and Currency Crashes," in *NBER Macroeconomics Annual 2008*, ed. by K. Rogoff, M. Woodford, and D. Acemoglu, Cambridge, MA: MIT Press, 23, 313–347.

Burnside, C. (2011): "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk: a Comment," *American Economic Review*, 101, 3456–3476.

Caballero, R. J., E. Farhi, and P.-O. Gourinchas (2008): "Financial Crash, Commodity Prices, and Global Imbalances," *Brookings Papers on Economic Activity*, 2008, 1–55.

Cespa, G., A. Gargano, S. J. Riddiough, and L. Sarno (2022): "Foreign Exchange Volume," *The Review of Financial Studies*, 35, 2386–2427.

Chernov, M., M. Dahlquist, and L. A. Lochstoer (2022): "Pricing Currency Risks," *Journal of Finance, forthcoming.*

Cochrane, J. (2005): *Asset Pricing*, NJ: Princeton University Press.

Cochrane, J. H. (2017): "Macro-Finance," *Review of Finance*, 21, 945–985.

Colacito, R., S. Riddiough, and L. Sarno (2020): "Business Cycles and Currency Returns," *Journal of Financial Economics*, 137, 659–678.

Dahlquist, M. and H. Hasseltoft (2020): "Economic Momentum and Currency Returns," *Journal of Financial Economics*, 136, 152–167.

Della Corte, P., R. Kozhan, and A. Neuberger (2021): "The cross-section of currency volatility premia," *Journal of Financial Economics*, 139, 950–970.

Della Corte, P., T. Ramadorai, and L. Sarno (2016a): "Volatility Risk Premia and Exchange Rate Predictability," *Journal of Financial Economics*, 120, 21–40.

Della Corte, P., S. J. Riddiough, and L. Sarno (2016b): "Currency Premia and Global Imbalances," *Review of Financial Studies*, 29, 2161–2193.

Dew-Becker, I., S. Giglio, A. Le, and M. Rodriguez (2017): "The Price of Variance Risk," *Journal of Financial Economics*, 123, 225–250.

Fama, E. F. and K. R. French (1993): "Common Risk Factors in the Returns of Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

——— (2015): "A Five-Factor Asset Pricing Model," *Journal of Financial Economics*, 116, 1–22.

Fama, E. F. and J. D. MacBeth (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, 607–636.

Feng, G., S. Giglio, and D. Xiu (2020): "Taming the Factor Zoo: A Test of New Factors," *Journal of Finance*, 75, 1327–1370.

Fratzscher, M., D. Rime, L. Sarno, and G. Zinna (2015): "The Scapegoat Theory of Exchange Rates: The First Tests," *Journal of Monetary Economics*, 70, 1–21.

Gabaix, X. and M. Maggiori (2015): "International Liquidity and Exchange Rate Dynamics," *Quarterly Journal of Economics*, 130, 1369–1420.

Giacoletti, M., K. T. Laursen, and K. J. Singleton (2021): "Learning from Disagreement in the U.S. Treasury Bond Market," *Journal of Finance*, 76, 395–441.

Giglio, S., B. Kelly, and D. Xiu (2021a): "Factor Models, Machine Learning, and Asset Pricing," *Annual Review of Financial Economics, forthcoming.*

Giglio, S., Y. Liao, and D. Xiu (2021b): "Thousands of Alpha Tests," *Review of Financial Studies*, 34, 3456–3496.

Giglio, S. and D. Xiu (2021): "Asset Pricing with Omitted Factors," *Journal of Political Economy*, 129, 1947–1990.

Giglio, S., D. Xiu, and D. Zhang (2021c): "Test Assets and Weak Factors," Working Paper 29002, National Bureau of Economic Research.

Gonzalez-Urteaga, A. and G. Rubio (2016): "The Cross-Sectional Variation of Volatility Risk Premia," *Journal of Financial Economics*, 119, 353–370.

Gourinchas, P. O., W. Ray, and D. Vayanos (2020): "A Preferred-Habitat Model of Term Premia and Currency Risk," mimeo, London School of Economics.

Greenwood, R., S. Hanson, J. Stein, and A. Sunderam (2020): "A Quantity-Driven Theory of Term Premia and Exchange Rates," NBER Working Papers 27615, National Bureau of Economic Research, Inc.

Harvey, C. R. and Y. Liu (2021): "Lucky Factors," *Journal of Financial Economics*, 141, 413–435.

Harvey, C. R., Y. Liu, and H. Zhu (2016): "...and the Cross-Section of Expected Returns," *Review of Financial Studies*, 29, 5–68.

Hassan, T. A. (2013): "Country Size, Currency Unions, and International Asset Returns," *Journal of Finance*, 68, 2269–2308.

He, Z., B. Kelly, and A. Manela (2017): "Intermediary Asset Pricing: New Evidence From Many Asset Classes," *Journal of Financial Economics*, 126, 1–35.

Hu, G. X., J. Pan, and J. Wang (2013): "Noise as Information for Illiquidity," *Journal of Finance*, 68, 2341–2382.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): "Measuring Uncertainty," *American Economic Review*, 105, 1177–1216.

Karnaukh, N., A. Ranaldo, and P. Söderlind (2015): "Understanding FX Liquidity," *Review of Financial Studies*, 28, 3073–3108.

Koijen, R. S., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt (2018): "Carry," *Journal of Financial Economics*, 127, 197–225.

Kozak, S., S. Nagel, and S. Santosh (2020): "Shrinking the Cross-Section," *Journal of Financial Economics*, 135, 271–292.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012): "The Aggregate Demand for Treasury Debt," *Journal of Political Economy*, 120, 233–267.

Kroencke, T., F. Schindler, and A. Schrimpf (2014): "International Diversification Benefits with Foreign Exchange Investment Styles," *Review of Finance*, 18, 1847–1883.

Lane, P. and G. Milesi-Ferretti (2004): "The External Wealth of Nations: Measures of Foreign Assets and Liabilities for Industrial and Developing Countries," *Journal of International Economics*, 55, 263–294.

——— (2007): "The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970-2004," *Journal of International Economics*, 73, 223–250.

Lettau, M., M. Maggiori, and M. Weber (2014): "Conditional Risk Premia in Currency Markets and Other Asset Classes," *Journal of Financial Economics*, 114, 197–225.

Lettau, M. and M. Pelger (2020a): "Estimating Latent Asset-Pricing Factors," *Journal of Econometrics*, 218, 1–30.

——— (2020b): "Factors that Fit the Time Series and Cross-section of Stock Returns," *Review of Financial Studies*, 33, 2274–2325.

Lewellen, J., S. Nagel, and J. Shanken (2010): "A Skeptical Appraisal of Asset Pricing Tests," *Journal of Financial Economics*, 96, 175–194.

Lintner, J. (1965): "Security Prices, Risk, and Maximal Gains from Diversification," *Journal of Finance*, 20, 587–615.

Lustig, H., N. Roussanov, and A. Verdelhan (2011): "Common Risk Factors in Currency Markets," *Review of Financial Studies*, 24, 3731–3777.

Lustig, H., A. Stathopoulos, and A. Verdelhan (2019): "The Term Structure of Currency Carry Trade Risk Premia," *American Economic Review*, 109, 4142–77.

Lustig, H. and A. Verdelhan (2007): "The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk," *American Economic Review*, 97, 89–117.

Maggiori, M. (2017): "Financial Intermediation, International Risk Sharing, and Reserve Currencies," *American Economic Review*, 107, 3038–71.

Malloy, C. J., T. J. Moskowitz, and A. Vissing-Jorgensen (2009): "Long-Run Stockholder Consumption Risk and Asset Returns," *Journal of Finance*, 64, 2427–2479.

Mark, N. C. (1995): "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability," *American Economic Review*, 85, 201–218.

Meese, R. and K. Rogoff (1983): "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics*, 14, 3–24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a): "Carry Trades and Global Foreign Exchange Volatility," *Journal of Finance*, 67, 681–718.

——— (2012b): "Currency Momentum Strategies," *Journal of Financial Economics*, 106, 681–718.

——— (2016): "Information Flows in Foreign Exchange Markets: Dissecting Customer Currency Trades," *Journal of Finance*, 71, 601–634.

——— (2017): "Currency Value," *Review of Financial Studies*, 30, 416–441.

Merton, R. C. (1973): "An Intertemporal Capital Asset Pricing Model," *Econometrica*, 41, 867–887.

Miranda-Agrippino, S. and H. Rey (2020): "U.S. Monetary Policy and the Global Financial Cycle," *Review of Economic Studies*, 87, 2754–2776.

Mueller, P., A. Tahbaz-Salehi, and A. Vedolin (2017): "Exchange Rates and Monetary Policy Uncertainty," *Journal of Finance*, 72, 1213–1252.

Onatski, A. (2010): "Determining the Number of Factors from Empirical Distribution of Eigenvalues," *Review of Economics and Statistics*, 92, 1004–1016.

Pastor, L. and R. Stambaugh (2003): "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111, 642–685.

Pastor, L. and P. Veronesi (2013): "Political Uncertainty and Risk Premia," *Journal of Financial Economics*, 110, 520–545.

Ranaldo, A. and P. Söderlind (2010): "Safe Haven Currencies," *Review of Finance*, 14, 385–407.

Ranaldo, A. and F. Somogyi (2021): "Asymmetric information risk in FX markets," *Journal of Financial Economics*, 140, 391–411.

Ready, R., N. Roussanov, and C. Ward (2017): "Commodity Trade and the Carry Trade: A Tale of Two Countries," *Journal of Finance*, 72, 2629–2684.

Rossi, B. (2013): "Exchange Rate Predictability," *Journal of Economic Literature*, 51, 1063–1119.

Shanken, J. (1992): "On the Estimation of Beta Pricing Models," *Review of Financial Studies*, 5, 1–34.

Sharpe, W. (1964): "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk," *Journal of Finance*, 19, 425–442.

Verdelhan, A. (2018): "The Share of Systematic Risk in Bilateral Exchange Rates," *Journal of Finance*, 73, 375–418.

Zviadadze, I. (2017): "Term Structure of Consumption Risk Premia in the Cross Section of Currency Returns," *Journal of Finance*, 72, 1529–1566.

Table 1: Latent factor pricing diagnostics

The table presents model diagnostics of the first two steps of the asset pricing procedure of Giglio and Xiu (2021) applied to currency portfolios excess returns, where the pricing factors are latent and are estimated using the RP-PCA method of Lettau and Pelger (2020a,b). We report diagnostics for RP-PCA implemented without "overweight" on the means ($\omega = -1$), that is, standard PCA, and with increasing values of the RP-weight ($\omega = 10$, 20 and 50). We consider SDFs, $\varphi(F_{1-k})$, including an increasing number of latent factors, $k = 1, 2, \ldots, 6$. Tab A.I First pass, Panel A: Two-pass Statistics, shows the average idiosyncratic variance, $\overline{\sigma}^2_\epsilon = \frac{1}{N}\sum_{n=1}^{N}[Var(\hat{\epsilon}_n)/Var(X_n)]$, and the average root-mean-square pricing errors, $\overline{RMS}_\alpha = \sqrt{\hat{\alpha}\hat{\alpha}^\top/N}$, obtained by estimating $X_{nt} = \alpha_n + \hat{F}_t\psi_n^\top + \epsilon_{nt}$, for $n = 1..., N$ test assets, and $t = 1..., T$. Tab A.II Second pass presents the R-squared values ($R^2(\%)$), and the mean absolute errors (MAE) of the cross-sectional regression, $\overline{X}_n = \hat{\psi}_n\gamma^\top + a_n$, for $n = 1, \ldots, N$, where γ is the $1 \times K$ vector of latent factors' prices of risk. Tab B.I Components, Panel B: Sharpe Ratios, presents the annualized maximal Sharpe ratio (SR) from the tangency portfolio of the mean-variance frontier spanned by the linear combination of the K selected latent factors, $\hat{F} \times \hat{b}_{MV}^\top$, where $\hat{b}_{MV}$ is a $1 \times$ K vector with entries $\hat{b}_{MV,k} = \mu_{F,k}/\sigma^2_{F,k}$, with $\mu_{F,k}$ and $\sigma^2_{F,k}$ denoting the k-th factor's annualized mean and variance. The means (in %) are starred with ***,**,* denoting significance at the 1, 5 and 10% levels, respectively, based on Newey-West standard errors. ΔSR denotes the difference in SRs between SDFs with k and $k-1$ factors. The $\hat{b}_{MV,k}$ entry represents the k-th factor's weight in the SDF, $\varphi_t = 1 - (\hat{F}_t - \mu_F)\hat{b}_{MV}^\top$. The test assets consist of the portfolios from the nine investment strategies ($N = 46$) – see Section II in the Internet Appendix – for the period from November 1983 to December 2017 at monthly frequency ($T = 410$).

	Panel A: Two-pass Statistics					Panel B: Sharpe Ratios			
	A.I First pass		A.II Second pass			B.I Components			
$\omega = -1$	$\overline{\sigma}^2_\epsilon$	$\overline{RMS}_\alpha$	$R^2(\%)$	MAE		SR	ΔSR	$\hat{b}_{MV,k}$	$\mu_{F,k}$
$\varphi(F_1)$	23.41	1.73	0.17	1.38	F_1	0.33	0.33	0.05	17.38*
$\varphi(F_{1-2})$	19.04	1.59	16.48	1.22	F_2	0.50	0.17	0.25	4.63**
$\varphi(F_{1-3})$	17.07	1.30	44.94	0.94	F_3	0.90	0.40	0.75	6.25***
$\varphi(F_{1-4})$	15.46	1.30	44.96	0.94	F_4	0.90	0.00	0.03	0.21
$\varphi(F_{1-5})$	14.12	0.91	72.06	0.73	F_5	1.28	0.38	1.10	6.26***
$\varphi(F_{1-6})$	12.92	0.90	72.37	0.71	F_6	1.28	0.00	0.14	0.71
$\omega = 10$	$\overline{\sigma}^2_\epsilon$	$\overline{RMS}_\alpha$	$R^2(\%)$	MAE		SR	ΔSR	$\hat{b}_{MV,k}$	$\mu_{F,k}$
$\varphi(F_1)$	23.42	1.73	29.02	1.24	F_1	0.35	0.35	0.06	18.12*
$\varphi(F_{1-2})$	19.44	1.53	77.94	0.59	F_2	0.98	0.63	0.70	10.02***
$\varphi(F_{1-3})$	17.31	0.89	97.22	0.22	F_3	1.51	0.53	1.13	9.70***
$\varphi(F_{1-4})$	15.79	0.71	98.49	0.17	F_4	1.61	0.10	0.63	4.05***
$\varphi(F_{1-5})$	14.19	0.70	98.54	0.16	F_5	1.61	0.00	0.13	0.89
$\varphi(F_{1-6})$	12.99	0.70	98.55	0.16	F_6	1.61	0.00	0.05	0.28
$\omega = 20$	$\overline{\sigma}^2_\epsilon$	$\overline{RMS}_\alpha$	$R^2(\%)$	MAE		SR	ΔSR	$\hat{b}_{MV,k}$	$\mu_{F,k}$
$\varphi(F_1)$	23.43	1.74	59.88	1.14	F_1	0.36	0.36	0.06	18.65**
$\varphi(F_{1-2})$	19.94	1.47	94.58	0.29	F_2	1.23	0.87	1.02	11.29***
$\varphi(F_{1-3})$	17.36	0.84	99.16	0.12	F_3	1.57	0.34	0.87	9.17***
$\varphi(F_{1-4})$	15.81	0.68	99.53	0.09	F_4	1.65	0.08	0.57	3.71***
$\varphi(F_{1-5})$	14.21	0.68	99.53	0.09	F_5	1.65	0.00	0.07	0.51
$\varphi(F_{1-6})$	13.01	0.68	99.53	0.09	F_6	1.65	0.00	0.05	0.27
$\omega = 50$	$\overline{\sigma}^2_\epsilon$	$\overline{RMS}_\alpha$	$R^2(\%)$	MAE		SR	ΔSR	$\hat{b}_{MV,k}$	$\mu_{F,k}$
$\varphi(F_1)$	23.51	1.76	90.70	0.87	F_1	0.39	0.39	0.06	19.67**
$\varphi(F_{1-2})$	20.36	1.37	99.26	0.11	F_2	1.39	1.00	1.25	11.85***
$\varphi(F_{1-3})$	17.40	0.80	99.85	0.05	F_3	1.61	0.22	0.67	8.29***
$\varphi(F_{1-4})$	15.83	0.67	99.91	0.04	F_4	1.68	0.07	0.52	3.46***
$\varphi(F_{1-5})$	14.23	0.66	99.91	0.04	F_5	1.68	0.00	0.06	0.38
$\varphi(F_{1-6})$	13.02	0.66	99.91	0.04	F_6	1.68	0.00	0.05	0.26

Table 2: Exposures of nontradable factors to latent factors

The table presents the nontradable candidate factors' exposures to the latent factors (η_{F_k}) and the explained variations ($R^2_{F_{1-k}}$) obtained from the spanning regression of Equation (15), for SDFs including an increasing number of factors, $k = 1, \ldots, K$. We report the candidate factor exposures to the first six extracted, orthogonalized latent factors ($K = 6$). The factors are extracted by applying RP-PCA with baseline weight ($\omega = 20$) to the $N = 46$ portfolios obtained from the nine investment strategies. Panels A, B, and C show the estimates for the financial, text-based, and macro factors, respectively. These factors are expressed as innovations, using the residuals from AR(1) processes, and are then standardized. We present the estimates only for the candidate factors with statistically significant risk premiums ($\hat{\lambda}_g$) according to the three-pass model with optimal number of factors, that is, $\varphi(F_{1-3})$, reported later in Table 3. When a macro factor's risk premium is significant at multiple frequencies, we present only the most representative one (the frequency at which the factor's risk premium is most precisely estimated). We report all candidate factors' exposures in Table A10, in the Internet Appendix. ***,**,* denote significance, respectively, at the 1, 5 and 10% levels, based on Newey-West standard errors. See nontradable factor descriptions in Tables A5–A7, in the Internet Appendix.

	Panel A: Financial Factors											
	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}	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$
otic	0.73**	5.73***	-0.35	-1.42	2.26	7.47**	1.17	3.67	3.68	3.77	4.01	5.99
noise	-1.36*	-11.34***	11.34**	8.06*	-0.62	-0.41	4.99	10.98	17.33	20.05	20.07	20.07
sliq	-1.29**	-10.48***	5.28	7.79*	-0.90	-6.67*	5.81	11.47	13.40	16.21	16.23	17.60
gfc	3.13***	11.71***	-7.49***	-2.96	8.80***	3.13	21.83	32.33	36.43	36.83	40.49	40.84
gvol	-1.07**	-9.95***	2.99	7.80**	-2.07	-8.34***	2.55	10.13	10.79	13.54	13.74	16.21
psliq	0.03	8.00**	-0.85	-0.88	2.42	-0.84	0.00	4.91	4.96	5.00	5.27	5.30
ted	-0.45	-6.82*	-0.44	0.38	0.72	0.27	0.47	3.94	3.95	3.96	3.98	3.98
lib ois	-1.48*	-14.14*	3.61	1.30	6.90	4.52	6.39	16.00	16.97	17.09	18.03	18.35
move	-0.98**	-10.89***	7.81***	0.12	-0.25	-1.94	2.78	8.33	11.75	11.75	11.75	11.86
vxo	-1.60***	-15.19***	10.32***	1.85	-6.91***	-1.35	6.47	19.96	26.40	26.55	28.50	28.56
eqrv	-0.65	-11.72**	1.46	3.11	-2.83	0.80	0.93	11.45	11.6	12.04	12.42	12.44
geqrv	-1.11***	-7.55*	-0.72	4.19*	-0.99	4.82	2.76	7.13	7.17	7.96	8.01	8.84
	Panel B: Text-Based Factors											
	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}	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$
gepu	0.00	-11.18***	3.38	3.12	-3.68	-3.52	1.12	7.36	7.64	7.99	8.26	8.56
gepu ppp	0.13	-12.01***	3.82	2.81	-3.79	-2.97	0.89	7.82	8.17	8.45	8.75	8.97
emv ov	-0.49	-9.13**	2.88	1.87	-1.51	0.31	0.48	6.73	7.35	7.51	7.61	7.61
emv mout	-0.38	-9.09**	2.19	2.74	-0.31	1.32	0.29	6.40	6.73	7.07	7.07	7.14
emv mqnt	-0.26	-7.85**	1.35	2.55	-1.12	1.09	0.14	4.78	4.92	5.21	5.27	5.31
emv inf	-0.28	-7.93**	2.92	0.09	-0.98	0.29	0.14	4.85	5.45	5.45	5.50	5.50
emv com	-0.55	-8.96**	3.64	1.21	-1.67	0.39	0.59	6.60	7.56	7.63	7.75	7.76
emv ir	-0.23	-7.97**	0.89	1.32	-1.56	1.60	0.11	4.96	5.03	5.11	5.22	5.31
emv fc	-0.72	-6.25*	2.52	2.78	2.96	-2.17	1.06	3.80	4.16	4.50	4.90	5.06
emv fp	-0.32	-7.32**	1.52	1.15	-1.58	0.34	0.21	4.29	4.48	4.54	4.65	4.65
emv tx	-0.34	-7.72**	2.09	2.10	-0.68	0.61	0.23	4.68	4.99	5.19	5.21	5.22
emv mp	-0.59	-8.69***	2.80	2.88	0.22	1.18	0.70	6.22	6.74	7.11	7.11	7.16
emv reg	-0.20	-8.56**	1.84	2.19	1.49	0.19	0.07	5.42	5.63	5.84	5.93	5.93
emv freg	-0.49	-7.54*	1.32	2.18	1.18	2.37	0.47	4.60	4.70	4.91	4.96	5.16
	Panel C: Macro Factors											
	C.I: Risk Exposures						C.II: Explained Variation					
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	$R^2_{F_1}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$
cus(y)	-0.69	-2.24	-1.54	-0.92	-0.08	1.49	1.06	1.45	1.62	1.66	1.66	1.74
ipw(q)	0.23	-2.60	-1.80	0.53	0.95	1.87	0.12	0.63	0.87	0.88	0.92	1.05
ipw/us(q)	-0.15	-3.69**	-1.40	1.39	-0.88	1.99	0.05	1.09	1.24	1.32	1.36	1.50
cpiw(q)	0.10	-1.25	-4.07***	0.51	-0.17	-2.67	0.02	0.14	1.35	1.36	1.36	1.61
cpiw/us(ey)	-0.36	-1.77	-2.58	-1.97	2.08	-2.59	0.28	0.52	1.01	1.18	1.39	1.63
unew/us(y)	-0.27	-1.99	-3.66**	-2.53	-0.64	1.37	0.16	0.47	1.46	1.75	1.77	1.83

Table 3: Risk premiums of nontradable factors

The table presents the risk-premium estimates of selected nontradable factors (g_t). Panel FMB presents the risk-premium point estimates (λ_g) and Shanken standard errors (se) from the standard two-pass procedure, including the constant and the candidate factor. The remaining panels report the estimates from the augmented three-pass models of different dimensions. That is, $\varphi(F_{1-k})$ denotes the SDF including up to the k-th latent factor, whereby the factors are extracted from the panel of currency portfolio returns using the RP-PCA method with baseline weight, i.e., $\omega = 20$. The risk-premium estimates (λ_g) are reported along with the asymptotic standard errors (se) of Giglio and Xiu (2021); ***,**,* denote significance, respectively, at the 1, 5 and 10% levels. For each factor and a given SDF, we also report the spanning R^2s (R2) resulting from projecting the factor onto the k latent factors entering the SDF; the annualized Sharpe ratios (SR) associated with the projected factor, i.e., the return-based counterpart to the original nontradable factor; and the p-value (pval) of the test of GX that the g-factor is weak. In Panels A, B and C, we present financial (FIN), text-based (TXT), and macro (MAC) candidate g-factors with significant risk-premium estimates according to at least one of the SDF reported. When a macro factor is significant for multiple frequencies, we present the frequency at which the factor is most precisely estimated using $\varphi(F_{1-3})$. Factors are expressed as innovations, using the residuals from AR(1) processes, and are then standardized. The sample period varies with the factor at hand, according to data availability over the period from November 1983 to December 2017. See nontradable factor descriptions in Tables A5–A7, in the Internet Appendix.

PANEL A:	FMB		$\varphi(F_{1-2})$					$\varphi(F_{1-3})$					$\varphi(F_{1-4})$				
FIN	λ_g	se	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval
otic	8.36***	(2.87)	0.78***	(0.27)	3.67	1.17	0.00	0.75**	(0.32)	3.68	1.12	0.00	0.70**	(0.33)	3.77	1.03	0.01
icap	3.41**	(1.56)	1.20***	(0.34)	7.93	1.23	0.00	0.61	(0.39)	10.91	0.53	0.00	0.76*	(0.43)	11.60	0.64	0.00
noise	-3.95***	(1.33)	-1.41***	(0.43)	11.27	1.10	0.00	-0.83**	(0.35)	16.33	0.33	0.01	-0.52	(0.41)	19.51	0.10	0.01
sliq	-3.56**	(1.46)	-1.33***	(0.38)	10.33	1.08	0.00	-0.91**	(0.39)	13.13	0.53	0.01	-0.48	(0.51)	17.65	0.23	0.00
gfc	2.39**	(1.09)	1.91***	(0.45)	32.33	0.97	0.00	1.22**	(0.52)	36.43	0.58	0.00	1.11*	(0.56)	36.83	0.53	0.00
gliq	-4.28	(3.25)	-0.44**	(0.19)	1.17	1.18	0.03	-0.11	(0.23)	2.10	0.23	0.01	-0.11	(0.24)	2.10	0.22	0.01
gvol	-4.19**	(1.57)	-1.32***	(0.32)	10.13	1.20	0.00	-1.05***	(0.30)	10.79	0.92	0.00	-0.76**	(0.36)	13.54	0.59	0.00
psliq	7.64***	(2.58)	0.91**	(0.36)	4.91	1.18	0.04	0.83*	(0.43)	4.96	1.08	0.06	0.80*	(0.45)	5.00	1.03	0.10
corp	-2.03	(1.57)	-0.87**	(0.41)	7.86	0.82	0.13	-0.10	(0.32)	14.60	0.07	0.10	-0.05	(0.34)	14.73	0.12	0.11
ted	-12.27***	(3.49)	-0.89**	(0.43)	3.98	1.23	0.14	-0.97**	(0.43)	4.05	1.35	0.21	-0.97**	(0.42)	4.05	1.34	0.33
lib ois	-4.71**	(1.86)	-1.88*	(0.99)	14.32	1.15	0.09	-1.55**	(0.76)	15.23	0.84	0.12	-1.47*	(0.78)	15.31	0.81	0.16
move	-5.13***	(1.88)	-1.35***	(0.46)	7.75	1.18	0.02	-0.81**	(0.38)	11.85	0.43	0.00	-0.75**	(0.37)	11.96	0.38	0.00
vxo	-4.36***	(1.24)	-2.04***	(0.60)	20.22	1.17	0.00	-1.36**	(0.65)	26.98	0.48	0.00	-1.18*	(0.64)	27.98	0.38	0.00
eqrv	-5.74***	(1.82)	-1.44**	(0.63)	11.45	1.23	0.06	-1.31*	(0.71)	11.60	1.11	0.13	-1.19*	(0.70)	12.04	0.99	0.21
geqrv	-7.60***	(2.39)	-1.05**	(0.48)	7.10	1.14	0.01	-1.12*	(0.56)	7.14	1.22	0.02	-0.97*	(0.56)	7.95	0.99	0.03
PANEL B:	FMB		$\varphi(F_{1-2})$					$\varphi(F_{1-3})$					$\varphi(F_{1-4})$				
TXT	λ_g	se	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval
gepu	-8.12***	(2.67)	-1.52***	(0.43)	7.93	1.23	0.00	-1.41***	(0.48)	8.02	1.11	0.00	-1.18**	(0.52)	8.61	0.96	0.00
gepu ppp	-8.25***	(2.65)	-1.58***	(0.44)	8.35	1.23	0.00	-1.46***	(0.48)	8.45	1.11	0.00	-1.25**	(0.53)	8.96	0.97	0.00
epu all	-5.18**	(2.32)	-0.67*	(0.35)	2.89	1.14	0.09	-0.34	(0.40)	3.92	0.44	0.05	-0.18	(0.39)	4.93	0.17	0.01
epu mp	-7.62***	(2.65)	-0.70**	(0.33)	3.91	1.04	0.06	-0.59	(0.40)	4.02	0.85	0.07	-0.47	(0.39)	4.62	0.61	0.05
fsi tx	-4.06*	(2.27)	-0.71*	(0.38)	2.70	1.22	0.16	-0.27	(0.31)	4.44	0.36	0.07	-0.17	(0.30)	4.80	0.21	0.13
emv ov	-6.79***	(2.30)	-1.15**	(0.46)	6.90	1.23	0.05	-0.91*	(0.45)	7.44	0.90	0.09	-0.84*	(0.44)	7.67	0.80	0.15
emv mout	-7.25***	(2.37)	-1.11**	(0.45)	6.55	1.23	0.05	-0.95**	(0.43)	6.80	1.01	0.11	-0.86**	(0.42)	7.17	0.86	0.18
emv mqnt	-7.77***	(2.59)	-0.95**	(0.40)	4.85	1.22	0.06	-0.84**	(0.38)	4.97	1.04	0.13	-0.75*	(0.38)	5.32	0.88	0.21
emv inf	-7.62***	(2.73)	-0.97***	(0.35)	4.99	1.22	0.02	-0.72*	(0.40)	5.52	0.84	0.02	-0.71*	(0.39)	5.52	0.82	0.04
emv com	-6.37***	(2.24)	-1.15**	(0.45)	6.82	1.23	0.04	-0.84*	(0.47)	7.68	0.81	0.05	-0.79*	(0.46)	7.79	0.74	0.07
emv ir	-9.09***	(2.94)	-0.97**	(0.44)	5.03	1.22	0.06	-0.90*	(0.51)	5.07	1.12	0.10	-0.83	(0.51)	5.23	1.01	0.16
emv fc	-7.57***	(2.73)	-0.86	(0.54)	3.86	1.18	0.17	-0.68*	(0.35)	4.13	0.88	0.28	-0.62*	(0.31)	4.30	0.76	0.42
emv fx	-5.15**	(2.19)	-0.71**	(0.29)	2.81	1.20	0.04	-0.42	(0.30)	3.54	0.59	0.02	-0.52	(0.31)	3.96	0.72	0.02
emv fp	-8.41***	(2.93)	-0.91**	(0.40)	4.38	1.23	0.08	-0.78*	(0.40)	4.55	1.01	0.17	-0.73*	(0.40)	4.66	0.92	0.27
emv tx	-7.42***	(2.63)	-0.96**	(0.43)	4.82	1.23	0.10	-0.79*	(0.43)	5.07	0.96	0.18	-0.72*	(0.43)	5.29	0.84	0.29
emv gov	-15.41***	(5.72)	-0.49*	(0.28)	1.50	1.14	0.23	-0.53	(0.32)	1.52	1.25	0.40	-0.56*	(0.33)	1.56	1.32	0.43
emv mp	-7.18***	(2.41)	-1.12***	(0.38)	6.41	1.23	0.01	-0.91**	(0.35)	6.80	0.94	0.04	-0.82**	(0.34)	7.15	0.81	0.06
emv reg	-8.27***	(2.74)	-1.01*	(0.51)	5.56	1.21	0.11	-0.89*	(0.47)	5.67	1.05	0.20	-0.83*	(0.46)	5.85	0.95	0.31
emv freg	-9.00***	(2.96)	-0.96*	(0.51)	4.70	1.23	0.20	-0.88*	(0.48)	4.75	1.11	0.35	-0.81*	(0.46)	4.95	0.99	0.45
emv tp	-7.47**	(3.34)	-0.70**	(0.31)	2.54	1.23	0.07	-0.40	(0.37)	3.38	0.55	0.02	-0.43	(0.38)	3.41	0.59	0.05
PANEL C:	FMB		$\varphi(F_{1-2})$					$\varphi(F_{1-3})$					$\varphi(F_{1-4})$				
MAC	λ_g	se	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval	λ_g	se	R2	SR	pval
cus(y)	-13.49***	(4.14)	-0.38	(0.25)	1.45	0.92	0.12	-0.52*	(0.29)	1.62	1.18	0.15	-0.56*	(0.28)	1.66	1.25	0.25
ipw(q)	-6.27***	(1.96)	-0.25	(0.22)	0.63	0.91	0.32	-0.42*	(0.24)	0.87	1.29	0.25	-0.40	(0.26)	0.88	1.22	0.37
ipw/us(q)	-7.34***	(2.19)	-0.44**	(0.21)	1.09	1.23	0.10	-0.57**	(0.26)	1.24	1.49	0.14	-0.52*	(0.29)	1.32	1.31	0.19
cpiw(q)	-7.92***	(2.92)	-0.12	(0.21)	0.14	0.95	0.73	-0.50*	(0.28)	1.35	1.23	0.04	-0.48*	(0.28)	1.36	1.18	0.08
cpiw/us(ey)	-9.60***	(2.78)	-0.27	(0.23)	0.52	1.06	0.45	-0.50*	(0.28)	1.01	1.44	0.25	-0.58*	(0.30)	1.18	1.52	0.24
unew/us(y)	-16.91***	(4.95)	-0.27	(0.21)	0.47	1.16	0.37	-0.61**	(0.24)	1.46	1.46	0.06	-0.70***	(0.25)	1.75	1.54	0.06

Table 4: Simulation calibration and true values

The table reports all the inputs required in the calibration of the data-generating process. Panel A: $z^{\iota}_{it} = \hat{F}^{\iota}_t \xi_i^{\top} + \zeta_{it}$ reports: A.I the risk premia of the latent factors ($\hat{\gamma}$); A.II the risk exposures of the noisy demeaned z-factors to the demeaned latent factors ($\hat{\xi}$); and A.III the standard deviations of the noise in the z-factors (σ_{ζ}), the standard deviations of the de-noised z-factors ($\sigma_{\hat{z}}$), the signal-to-noise ratios ($\sigma^2_{\hat{z}}/\sigma^2_{\zeta}$), and the explained variations or spanning R^2s ($\sigma^2_{\hat{z}}/\sigma^2_{z}$). Panel B: $X_{nt} = \hat{\mathrm{Z}}_t \psi^{\top}_{Zn} + \varepsilon_{nt}$ reports the average, median, minimum, and maximum risk exposures of the N test assets to each of the four de-noised z-factors ($\hat{\psi}_Z$). Panel C: $g^{\iota}_{jt} = \hat{Z}^{\iota}_t \eta^{\top}_{Zj} + u_{jt}$ reports: C.I the risk premia of the de-noised z-factors ($\hat{\lambda}_Z$); C.II the risk exposures of the noisy candidate nontradable g-factors to the de-noised, demeaned z-factors ($\hat{\eta}_Z$); and C.III the standard deviations of the noise in the g-factors (σ_u), the standard deviations of the de-noised g-factors ($\sigma_{\hat{g}}$), the signal-to-noise ratios ($\sigma^2_{\hat{g}}/\sigma^2_u$), and the explained variations or spanning R^2s ($\sigma^2_{\hat{g}}/\sigma^2_g$). Panel D: *True* Risk Premia reports the target risk-premium parameters for the z- and g-factors: for each factor, the risk-premium estimate (λ), the associated asymptotic standard error (se), and the annualized Sharpe ratio (SR). The z-factors are the four tradable factors (dollar, carry, ST mom, and value), and the g-factors are the standardized AR(1) innovations to the selected nontradable factors (gvol, icap, and ipus). To obtain the de-noised factors that drive the data-generating process, we applied the baseline three-pass model with $\omega = 20$ and four latent factors. Based on this calibration, we then perform $M = 10,000$ artificial Monte Carlo realizations with $N = 46$ and $T = 410$, which match the cross-section and time-series dimensions of our baseline sample of FX portfolio returns.

Panel A: $z^{\iota}_{it} = \hat{F}^{\iota}_t \xi_i^{\top} + \zeta_{it}$

A.I: Risk Premia ($\hat{\gamma}$)

	$\hat{\gamma}_{F_1}$	$\hat{\gamma}_{F_2}$	$\hat{\gamma}_{F_3}$	$\hat{\gamma}_{F_4}$
$\hat{\gamma}_F$	0.187	0.113	0.092	0.037

A.II: Risk Exposures ($\hat{\xi}$)

	$\hat{\xi}_1$	$\hat{\xi}_2$	$\hat{\xi}_3$	$\hat{\xi}_4$
$\mathrm{z}_{\mathrm{dol}}$	0.137	0.017	-0.018	-0.014
$\mathrm{z}_{\mathrm{car}}$	0.000	0.730	0.196	0.080
$\mathrm{z}_{\mathrm{mom}}$	-0.004	-0.249	0.661	-0.141
$\mathrm{z}_{\mathrm{val}}$	0.021	0.026	0.074	0.762

A.III: Signal-to-Noise (z; $\hat{z}$; $\hat{\zeta}$)

	σ_{ζ}	$\sigma_{\hat{z}}$	$\sigma^2_{\hat{z}}/\sigma^2_{\zeta}$	$\sigma^2_{\hat{z}}/\sigma^2_{z}$
$\mathrm{z}_{\mathrm{dol}}$	0.019	0.246	175.218	0.994
$\mathrm{z}_{\mathrm{car}}$	0.135	0.258	3.667	0.786
$\mathrm{z}_{\mathrm{mom}}$	0.213	0.228	1.140	0.533
$\mathrm{z}_{\mathrm{val}}$	0.160	0.203	1.621	0.618

Panel B: $X_{nt} = \hat{\mathrm{Z}}_t \psi^{\top}_{Zn} + \varepsilon_{nt}$

B.I: Risk Exposures ($\hat{\psi}_Z$)

	$\hat{\psi}_{Z_{\mathrm{dol}}}$	$\hat{\psi}_{Z_{\mathrm{car}}}$	$\hat{\psi}_{Z_{\mathrm{mom}}}$	$\hat{\psi}_{Z_{\mathrm{val}}}$
mean	1.071	-0.014	-0.008	-0.027
med	1.071	-0.065	0.018	-0.012
min	0.664	-0.465	-0.533	-0.517
max	1.359	0.585	0.449	0.498

Panel C: $g^{\iota}_{jt} = \hat{Z}^{\iota}_t \eta^{\top}_{Zj} + u_{jt}$

C.I: Risk Premia ($\hat{\lambda}_Z$)

	$\hat{\lambda}_{Z_{\mathrm{dol}}}$	$\hat{\lambda}_{Z_{\mathrm{car}}}$	$\hat{\lambda}_{Z_{\mathrm{mom}}}$	$\hat{\lambda}_{Z_{\mathrm{val}}}$
$\hat{\lambda}_Z$	0.026	0.064	0.082	0.022

C.II: Risk Exposures ($\hat{\eta}_Z$)

	$\hat{\eta}_{Z_{\mathrm{dol}}}$	$\hat{\eta}_{Z_{\mathrm{car}}}$	$\hat{\eta}_{Z_{\mathrm{mom}}}$	$\hat{\eta}_{Z_{\mathrm{val}}}$
$\mathrm{g}^{\iota}_{\mathrm{gvol}}$	-5.275	-12.403	1.900	5.307
$\mathrm{g}^{\iota}_{\mathrm{icap}}$	4.265	11.128	-0.004	6.127
$\mathrm{g}^{\iota}_{\mathrm{ipus}}$	-2.435	1.665	1.932	0.885

C.III: Signal-to-Noise (g; $\hat{g}$; $\hat{u}$)

	σ_u	$\sigma_{\hat{g}}$	$\sigma^2_{\hat{g}}/\sigma^2_u$	$\sigma^2_{\hat{g}}/\sigma^2_g$
$\mathrm{g}^{\iota}_{\mathrm{gvol}}$	11.172	4.421	0.135	0.157
$\mathrm{g}^{\iota}_{\mathrm{icap}}$	11.288	4.089	0.116	0.131
$\mathrm{g}^{\iota}_{\mathrm{ipus}}$	11.980	1.024	0.007	0.007

Panel D: *True* Risk Premia

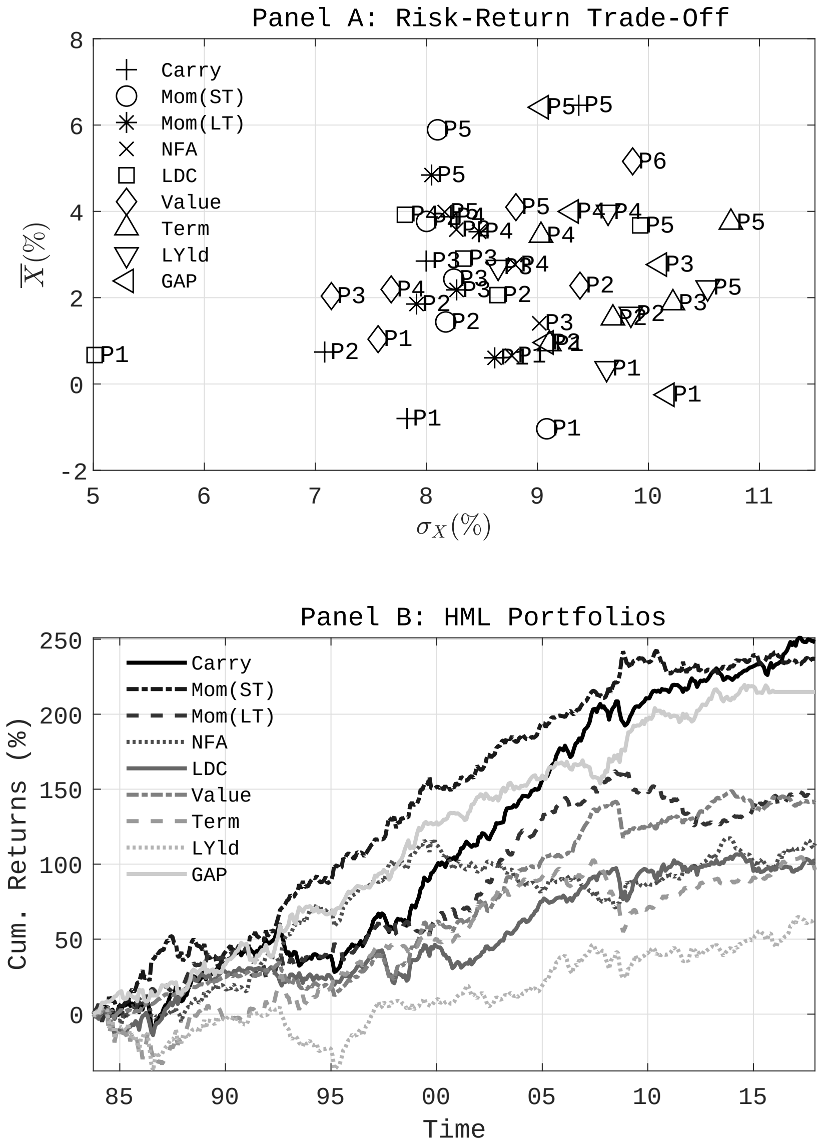
	$\hat{\lambda}_Z$	$\hat{\lambda}_G$	(se)	SR
$\mathrm{z}_{\mathrm{dol}}$	0.026	-	0.013	0.367
$\mathrm{z}_{\mathrm{car}}$	0.064	-	0.014	0.854
$\mathrm{z}_{\mathrm{mom}}$	0.082	-	0.012	1.249
$\mathrm{z}_{\mathrm{val}}$	0.022	-	0.010	0.369
$\mathrm{g}^{\iota}_{\mathrm{gvol}}$	-	-0.759	0.360	0.595
$\mathrm{g}^{\iota}_{\mathrm{icap}}$	-	0.756	0.430	0.641
$\mathrm{g}^{\iota}_{\mathrm{ipus}}$	-	0.159	0.385	0.539

Table 5: Three-pass simulation results

The table presents the three-pass estimates on simulated data, whereby the estimator uses baseline RP-weight ($\omega = 20$) and $k = 2, \ldots, 5$ latent factors ($\varphi(\hat{F}_{1-k})$). Thus, Panels A, B, C, and D refer to the two-, three-, four- and five-factor models, respectively. For a selected model, we focus on the following three objects: the candidate factor's annualized risk premium (λ), the associated asymptotic standard error (se), and the annualized Sharpe ratio of the factor de-noised counterpart (SR). Specifically, in each panel, Tab I reports the means of the estimates ($Estimate$); Tab II the standard deviations of the estimates (SD); Tab III the means of the biases ($Bias$), whereby the bias is given by the estimate minus the true value for the selected object; Tab IV the root-mean-square errors ($RMSE$). The true data generating process (DGP) has four factors, and the parameters are calibrated based on the four de-noised z-factors (dollar, carry, ST mom, and value). To remove noise from the factors, we applied the three-pass model with $\omega = 20$ and four latent factors ($\varphi(F_{1-4})$) to the panel of FX portfolio returns. The candidate factors include the four noisy z-factors (dollar, carry, ST mom, and value) and the innovations to the three noisy nontradable g-factors ($gvol$, $icap$, and $ipus$). The *true* values are reported in Table 4, along with the other calibrated parameters. The results are based on $M = 10,000$ artificial Monte Carlo realizations with $N = 46$ and $T = 410$.

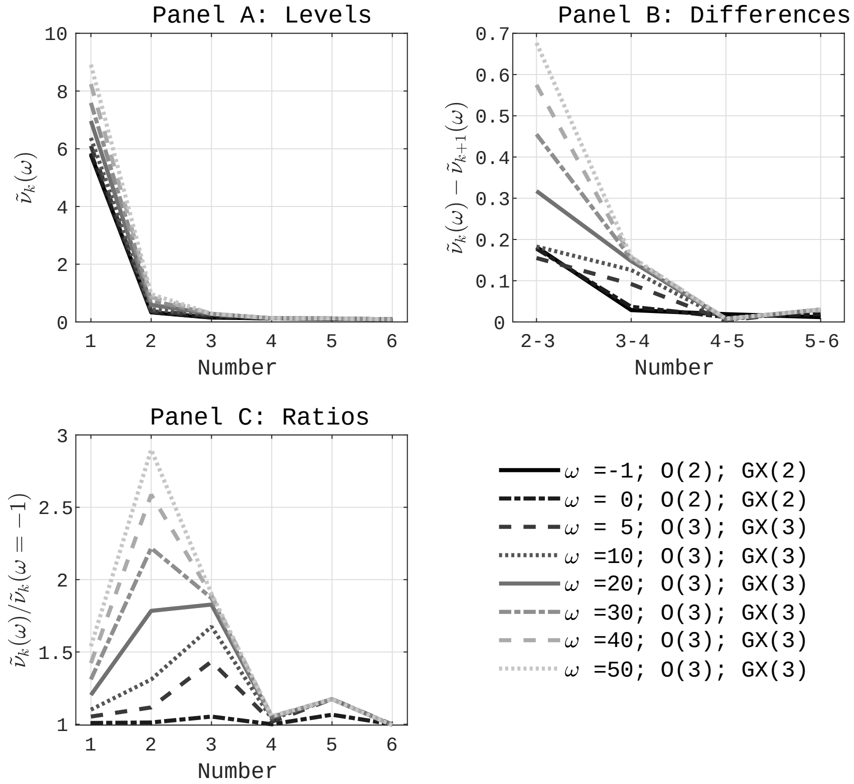
	A.I: Estimate			A.II: SD			A.III: Bias			A.IV: RMSE		
Panel A: Two-Factor Model, $\varphi(F_{1-2})$	λ	se	SR	λ	se	SR	λ	se	SR	λ	se	SR
z_{dol}	0.026	0.012	0.367	0.013	0.001	0.170	0.000	-0.001	0.001	0.013	0.001	0.170
z_{car}	0.089	0.012	1.409	0.017	0.001	0.234	0.025	-0.003	0.555	0.031	0.003	0.602
z_{mom}	0.033	0.007	1.091	0.024	0.002	0.395	-0.050	-0.005	-0.159	0.055	0.006	0.426
z_{val}	0.007	0.006	0.791	0.010	0.001	0.418	-0.015	-0.004	0.421	0.018	0.004	0.594
g^{ι}_{gvol}	-1.356	0.296	1.314	0.343	0.034	0.226	-0.597	-0.064	0.720	0.689	0.073	0.754
g^{ι}_{icap}	1.194	0.286	1.342	0.379	0.033	0.245	0.438	-0.144	0.701	0.579	0.148	0.742
g^{ι}_{ipus}	0.189	0.252	0.826	0.258	0.040	0.466	0.030	-0.133	0.288	0.260	0.139	0.548
Panel B: Three-Factor Model, $\varphi(F_{1-3})$	B.I: Estimate			B.II: SD			B.III: Bias			B.IV: RMSE		
	λ	se	SR	λ	se	SR	λ	se	SR	λ	se	SR
z_{dol}	0.025	0.012	0.362	0.012	0.001	0.169	-0.001	-0.001	-0.005	0.012	0.001	0.169
z_{car}	0.064	0.013	0.866	0.014	0.001	0.185	0.000	-0.001	0.012	0.014	0.001	0.185
z_{mom}	0.082	0.011	1.306	0.012	0.001	0.190	0.000	-0.001	0.057	0.012	0.001	0.198
z_{val}	-0.003	0.007	0.589	0.013	0.001	0.396	-0.024	-0.003	0.220	0.028	0.003	0.453
g^{ι}_{gvol}	-1.026	0.339	0.890	0.368	0.034	0.295	-0.267	-0.022	0.296	0.455	0.040	0.418
g^{ι}_{icap}	0.639	0.340	0.557	0.349	0.035	0.275	-0.118	-0.091	-0.084	0.368	0.097	0.288
g^{ι}_{ipus}	0.223	0.297	0.827	0.299	0.036	0.489	0.063	-0.088	0.288	0.305	0.095	0.568
Panel C: Four-Factor Model, $\varphi(F_{1-4})$	C.I: Estimate			C.II: SD			C.III: Bias			C.IV: RMSE		
	λ	se	SR	λ	se	SR	λ	se	SR	λ	se	SR
z_{dol}	0.026	0.012	0.368	0.012	0.001	0.169	0.000	-0.001	0.001	0.012	0.001	0.169
z_{car}	0.064	0.013	0.864	0.013	0.001	0.182	0.000	-0.001	0.010	0.013	0.001	0.182
z_{mom}	0.082	0.012	1.294	0.012	0.001	0.185	0.000	-0.001	0.045	0.012	0.001	0.190
z_{val}	0.014	0.010	0.360	0.015	0.001	0.221	-0.007	0.000	-0.010	0.017	0.001	0.221
g^{ι}_{gvol}	-0.843	0.353	0.672	0.376	0.035	0.289	-0.084	-0.007	0.078	0.385	0.036	0.299
g^{ι}_{icap}	0.724	0.348	0.608	0.356	0.035	0.276	-0.033	-0.082	-0.033	0.357	0.089	0.278
g^{ι}_{ipus}	0.178	0.306	0.680	0.307	0.036	0.445	0.019	-0.079	0.141	0.307	0.087	0.467
Panel D: Five-Factor Model, $\varphi(F_{1-5})$	D.I: Estimate			D.II: SD			D.III: Bias			D.IV: RMSE		
	λ	se	SR	λ	se	SR	λ	se	SR	λ	se	SR
z_{dol}	0.026	0.012	0.370	0.012	0.001	0.169	0.000	-0.001	0.004	0.012	0.001	0.169
z_{car}	0.064	0.013	0.866	0.013	0.001	0.180	0.001	-0.001	0.012	0.013	0.001	0.181
z_{mom}	0.083	0.012	1.300	0.012	0.001	0.182	0.001	-0.001	0.050	0.012	0.001	0.189
z_{val}	0.021	0.011	0.373	0.012	0.001	0.192	-0.001	0.001	0.004	0.012	0.001	0.192
g^{ι}_{gvol}	-0.779	0.359	0.600	0.363	0.034	0.264	-0.020	-0.001	0.006	0.363	0.034	0.264
g^{ι}_{icap}	0.756	0.352	0.624	0.354	0.035	0.273	-0.001	-0.078	-0.017	0.354	0.085	0.273
g^{ι}_{ipus}	0.164	0.311	0.614	0.310	0.036	0.416	0.005	-0.074	0.075	0.310	0.082	0.422

Figure 1: Currency Investment Strategies



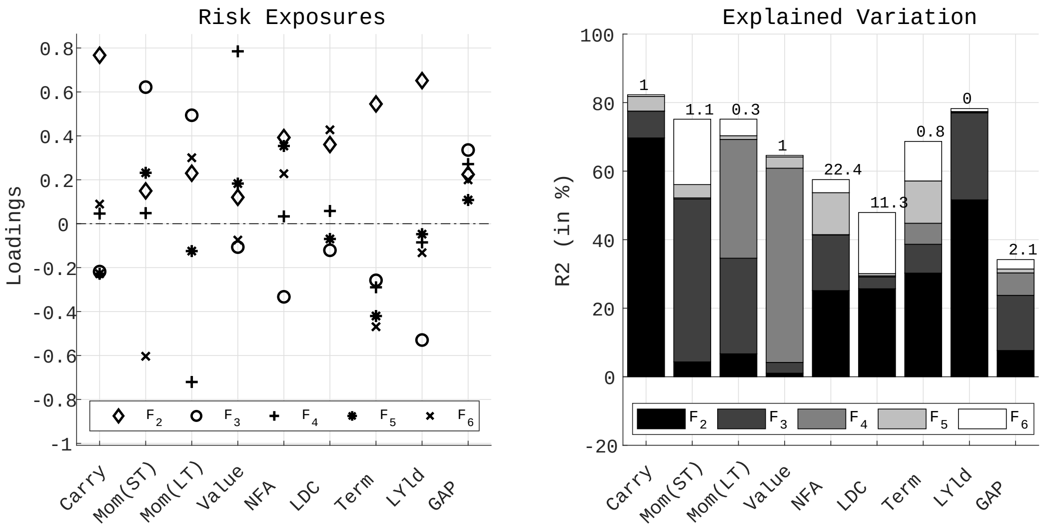
In Panel A, Risk-Return Trade-Off, the figure shows plain portfolio average excess returns ($\overline{X}(\%)$, in percent annualized) and standard deviations ($\sigma_X(\%)$, in percent annualized), proxying for risk. In Panel B, HML Portfolios, the figure plots the cumulative monthly returns of HML portfolios in percent. We consider nine investment strategies: carry (Carry), short-term momentum (Mom (ST)), long-term momentum (Mom (LT)), net foreign assets (NFA), liabilities in domestic currency (LDC), value (Value), term spreads (Term), long-term bond yields (LYld), and output gap (GAP). See Internet Appendix (Section II) for a detailed description of the strategies. The sample spans the 11/1983-12/2017 period at monthly frequency ($T = 410$).

Figure 2: Largest Normalized Eigenvalues



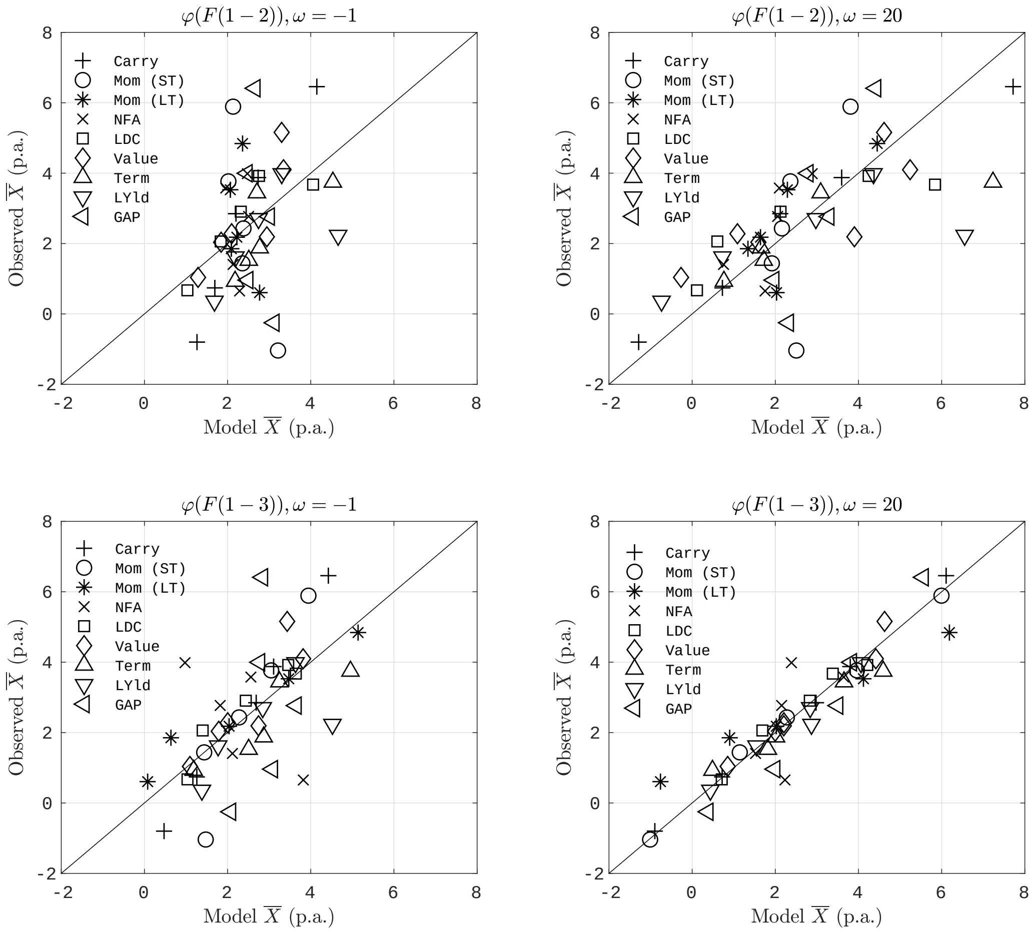
The figure shows the largest normalized eigenvalues of the matrix $\Sigma_{RP}^{(\omega)} = \frac{1}{T} X^\top X + \omega \overline{X}^\top \overline{X}$, for different values of the RP-weight (ω). The $T \times N$ matrix X collects currency portfolio excess returns from the nine investment strategies (i.e., $N = 46$), and $\overline{X}$ denote their sample averages. The eigenvalues are normalized by the average idiosyncratic variance ($\bar{\sigma}_\epsilon^2$) and hence relate more closely to factors' signal-to-noise ratios, being informative about factors' "signal strengths". Specifically, $\bar{\sigma}_\epsilon^2 = \frac{1}{N} \sum_{n=1}^{N} \sigma_{\epsilon,n}^2$, where $\sigma_{\epsilon,n}^2$ are the variances of the residuals obtained by estimating N time-series regressions, $X_{nt} = \alpha_n + \hat{F}_t^{(\omega)} \psi_n^\top + \epsilon_{nt}$, $n = 1..., N$ test assets, $t = 1..., T$ months, where $\hat{F}_t^{(\omega)}$ stacks the latent factors associated with the six largest eigenvalues of matrix $\Sigma_{RP}^{(\omega)}$, and thus vary with the RP-weight. Panel A, *Levels*, reports the normalized eigenvalues, $\tilde{\nu}_k(\omega) = \nu_k(\omega)/\sigma_\epsilon^2(\omega)$. Panel B, *Differences*, presents the difference of consecutive normalized eigenvalues, $\tilde{\nu}_k(\omega) - \tilde{\nu}_{k+1}(\omega)$, for $k = 2, \ldots, 5$. Panel C, *Ratios*, shows the eigenvalues scaled by the corresponding PCA ($\omega = -1$) eigenvalues, $\tilde{\nu}_k(\omega)/\tilde{\nu}_k(\omega = -1)$. In the legend, for a given RP-weight we present the optimal number of latent factors entering the SDF according to the Onatski (2010), O(#), and Giglio and Xiu (2021), GX(#), tests. The GX test is implemented with medium overfitting penalty value 0.5.

Figure 3: HML Portfolio Risk Exposures to Latent Factors



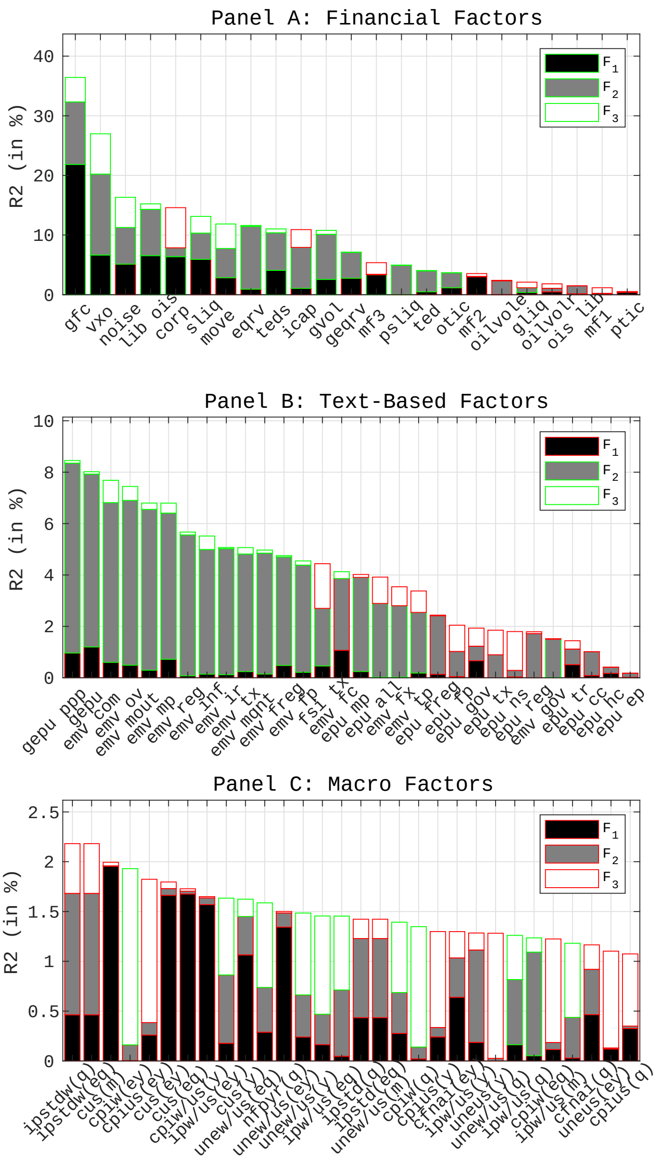
The figure shows HML portfolio loadings on the six estimated latent factors (Risk Exposures; left chart) and the associated R^2s obtained by regressing the HML portfolio returns on the latent factors (Explained Variation; right chart). The test assets' sample consists of the portfolios associated with the nine investment strategies ($N = 46$), thus HML portfolios are excluded from the estimation of latent factors (see Section II in the Internet Appendix for a description of the investment strategies). Hence, we infer HML portfolio loadings ex-post from the corner portfolio loadings of the associated strategy, as the difference between P5/6 (high) and P1 (low) loadings, obtained by means of RP-PCA with baseline penalty value, i.e., $\omega = 20$. We obtain the HML portfolios' explained variations by estimating 9×6 OLS time-series regressions of the type of Eq. (7), i.e., $X_{nt} = \alpha_n + \hat{F}_t \psi_n^\top + \epsilon_{nt}$, for $n = 1, \ldots, N$, and $t = 1, \ldots, T$. For a given HML portfolio, we run a total of 6 regressions as we include factors one by one. In this way, we can determine the marginal R^2 contributions of each factor. The numbers above the bars refer to $\hat{F}_{1t}$'s contributions. We present the $N \times K$ individual portfolio risk exposures and R^2s in Figures A1 and A2, in the Internet Appendix. The sample spans the 11/1983-12/2017 period at monthly frequency ($T = 410$).

Figure 4: Observed vs Model-Implied Portfolio Excess Returns



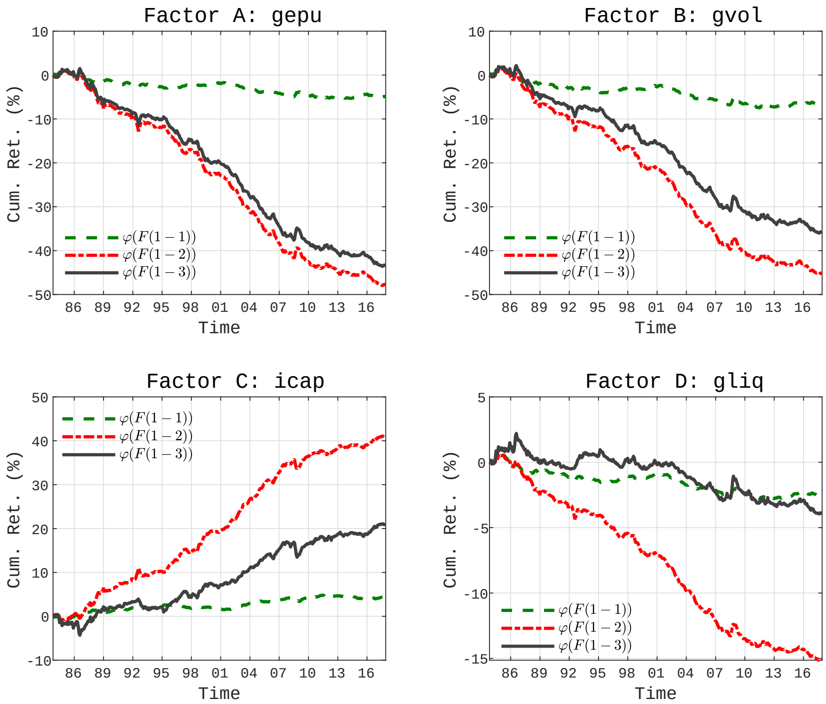
The figure shows the realized average excess returns (Observed $\overline{X}$, in percent annualized) and the estimated, model-implied expected excess returns (Model $\overline{X}$, in percent annualized) of the 46 currency portfolios (test assets) associated with the nine currency investment strategies, described in Section II in the Internet Appendix. For a given portfolio n, the model-implied expected excess returns are the fitted values from the second pass of the GX method. That is, the fitted return is given by $\hat{\psi}_{nk}\hat{\gamma}_k^\top$ where $\hat{\psi}_{nk}$ is the $1 \times k$ vector of the n-th portfolio's risk exposures and $\hat{\gamma}_k$ is the $1 \times k$ vector of the prices of risk of the k latent factors. Left panels show the evidence for the factors extracted using PCA (i.e., RP-PCA with $\omega = -1$), while right panels using RP-PCA with $\omega = 20$ (i.e., the selected RP-weight). Top panels present the estimates for $k = 2$, while bottom panels for $k = 3$. Recall that $\varphi(F(1-2))$ is the optimal SDF for $\omega = -1$, whereas $\varphi(F(1-3))$ for $\omega = 20$. Excess returns are expressed in percent per annum (p.a). The sample period runs from 11/1983 to 12/2017 at monthly frequency ($T = 410$).

Figure 5: Nontradable Factors' Explained Variation by Latent Pricing Factors



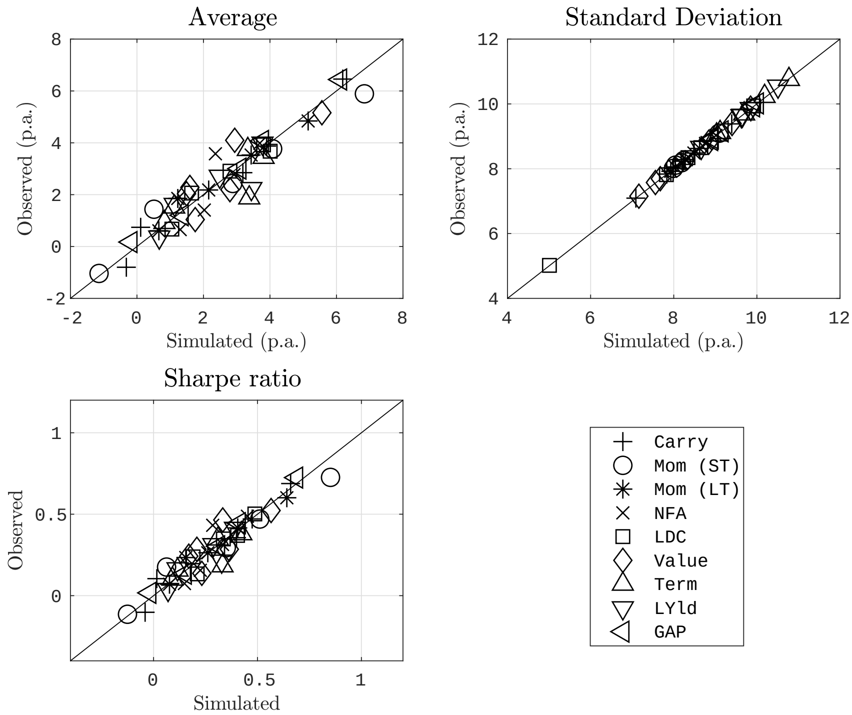
The figure shows nontradable candidate factors' explained variation by latent factors. Factors are extracted by means of RP-PCA with baseline RP-weight $\omega = 20$ applied to the panel of $N = 46$ currency portfolios associated with the nine investment strategies. We limit the evidence to the first three extracted factors, given that the optimal SDF is $\varphi(F_{1-k})$ with $k = 3$ (Figure A4 in the Internet Appendix uses $k = 6$). Panels A, B, and C present the evidence for financial, text-based and macro candidate factors, respectively. In each panel, candidate factors are sorted by the spanning R^2s associated with the k-factor SDF (to help visualize the results, we only display the 30 macro factors with the highest R^2s). Bars quantify the latent factor contribution to the overall R^2. Green (red) bar edges denote (not) significant risk premiums, at the 10 percent level, according to the selected SDF; we consider SDFs of expanding dimension, thus k ranges from 1 to 3. Nontradable factors are expressed as innovations, using the residuals from AR(1) processes, and are then standardized. The sample period varies with the factor at hand, according to data availability over the 11/1983-12/2017 period ($T = 410$). See factor descriptions in Tables A5-A7, in the Internet Appendix.

Figure 6: Return-Based Candidate Factors



The figure shows the cumulative returns of selected return-based candidate factors. Factor A is the global economic policy uncertainty index (gepu), Factor B is the global FX volatility factor (gvol), Factor C is the financial intermediaries' capital ratio factor (icap), and Factor D is the global FX liquidity factor (gliq). For each candidate factor, we present three versions of return-based factors, by expanding the dimension of the SDF, i.e., $\varphi(F(1-k))$ with $k = 1, 2, 3$. Specifically, for $\varphi(F(1-k))$, the return-based factor is given by $\hat{F}_{1:kt}\hat{\eta}^{\top}$, where the latent factors are extracted using RP-PCA with $\omega = 20$ and the exposures are obtained by estimating the spanning regressions of Eq. (15); hence, the underlying exposures are those displayed in the first three columns of Table 2 (for *icap* and *gliq*, see Table A10 in the Internet Appendix, as their premiums estimates are not statistically significant using the three-factor model). The spanning regression sample period can vary with the factor at hand, according to data availability over the 11/1983-12/2017 period. See factor descriptions in Tables A5-A7, in the Internet Appendix.

Figure 7: Observed vs. Simulated Test-Asset Return Moments



The figure shows the moments of the observed and simulated test-asset returns. In *Average*, we plot the time-series averages of the observed portfolio returns (*Observed*, in percent annualized) against the means of the time-series averages of the simulated portfolio returns (*Simulated*, in percent annualized); in *Standard Deviation*, we show the standard deviations of the observed returns against the means of the standard deviations of the simulated returns (in percent, annualized); in *Sharpe ratio*, we report the annualized Sharpe ratios of the observed returns against the means of the Sharpe ratios of the simulated returns. The observed cross-sectional standard deviation of the average returns is 0.0173, and the mean of the cross-sectional standard deviation of the simulated average returns is 0.0194. The true data generating process (DGP) has four factors, and the parameters are calibrated based on the four de-noised z-factors (Dollar, Carry, ST Mom, and Value). To de-noise the z-factors, we used RP-PCA with $\omega = 20$ and four pricing factors. We simulate the models 10,000 times with $N = 46$ and $T = 410$ (see Section VI and Table A24).

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2021

ACCETTURO A., A. LAMORGESE, S. MOCETTI and D. PELLEGRINO, *Housing Price elasticity and growth: evidence from Italian cities,* Journal of Economic Geography, v. 21, 3, pp. 367-396, **WP 1267 (March 2020).**

AFFINITO M. and M. PIAZZA, *Always look on the bright side? Central counterparties and interbank markets during the financial crisis*, International Journal of Central Banking, v. 17, 1, pp. 231-283, **WP 1181 (July 2018).**

ALBANESE G., E. CIANI and G. DE BLASIO, *Anything new in town? The local effects of urban regeneration policies in Italy,* Regional Science and Urban Economics, v. 86, **WP 1214 (April 2019).**

ALBANESE G., G. DE BLASIO and A. LOCATELLI, *Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno,* Papers in Regional Science, v. 100, 2, pp. 327-348, **WP 1253 (December 2019).**

ALBERTAZZI A., A. NOBILI and F. M. SIGNORETTI, *The bank lending channel of conventional and unconventional monetary policy,* Journal of Money, Credit and Banking, v. 53, 2-3, pp. 261-299, **WP 1094 (Jan 2017).**

ANZUINI A. and L. ROSSI, *Fiscal policy in the US: a new measure of uncertainty and its effects on the American economy*, Empirical Economics, v. 61, 6, pp. 2613-2634, **WP 1197 (November 2018).**

APRIGLIANO V. and D. LIBERATI, *Using credit variables to date business cycle and to estimate the probabilities of recession in real time*, The Manchester School, v. 89, 51, pp. 76-96, **WP 1229 (July 2019).**

AUER S., M. BERNARDINI and M. CECIONI, *Corporate leverage and monetary policy effectiveness in the euro area,* European Economic Review, v. 140, Article 103943, **WP 1258 (December 2019).**

BANERJEE R, L. GAMBACORTA and E. SETTE, *The real effects of relationship lending,* Journal of Financial Intermediation, v. 48, Article 100923, **WP 1133 (September 2017).**

BAMIEH O and A. CINTOLESI, *Intergenerational Transmission in regulated professions and the role of familism,* Journal of Economic Behavior & Organization, v. 192, pp. 857-879, **WP 1350 (October 2021).**

BARONE G., F. DAVID, G. DE BLASIO and S. MOCETTI, *How do house prices respond to mortgage supply?,* Journal of Economic Geography, v. 21, 1, pp.127-140, **WP 1282 (June 2020).**

BARONE G. and S. MOCETTI, *Intergenerational mobility in the very long run: Florence 1427-2011,* Review of Economic Studies, v. 88, 4, pp. 1863–1891, **WP 1060 (April 2016).**

BARTOCCI A., L. BURLON, A. NOTARPIETRO and M. PISANI, *Macroeconomic effects of non-standard monetary policy measures in the Euro Area: the role of corporate bond purchases,* The Manchester School, v. 89, S1, pp. 97-130, **WP 1241 (October 2019).**

BATINI N., A. CANTELMO, G. MELINA and S. VILLA, *How loose, how tight? A measure of monetary and fiscal stance for the euro area,* Oxford Economic Papers, v. 73, 4, pp. 1536-1556, **WP 1295 (September 2020).**

BENETTON M. and D. FANTINO, *Targeted monetary policy and bank lending behavior,* Journal of Financial Economics, v. 142, 1, pp. 404-429, **WP 1187 (September 2018).**

BUSETTI F., M. CAIVANO and D. DELLE MONACHE, *Domestic and global determinants of inflation: evidence from expectile regression,* Oxford Bulletin of Economics and Statistics, v. 83, 4, pp. 982-1001, **WP 1225 (June 2019).**

BUSETTI F., M. CAIVANO, D. DELLE MONACHE and C. PACELLA, *The time-varying risk of Italian GDP,* Economic Modelling, v. 101, Article 105522, **WP 1288 (July 2020).**

BUSETTI F., S. NERI, A. NOTARPIETRO and M. PISANI, *Monetary Policy strategies in the new normal: a model-based analysis for the Euro Area,* Journal of Macroeconomics, v. 70, Article 103366, **WP 1308 (December 2020).**

CAPOLONGO A. and C. PACELLA, *Forecasting inflation in the Euro Area: countries matter*, Empirical Economics, v. 61, 4, pp. 2477-2499, **WP 1224 (June 2019).**

CARMIGNANI A., G. DE BLASIO, C. DEMMA and A. D'IGNAZIO, *Urbanization and firm access to credit,* Journal of Regional Science, v. 61, 3, pp. 597-622, **WP 1222 (June 2019).**

CORNELI F., *Financial integration without financial development,* Atlantic Economic Journal, v. 49, 2, pp. 201-220, **WP 1120 (June 2017).**

COVA P., P. PAGANO, A. NOTARPIETRO and M. PISANI, *Secular stagnation, R&D, public investment and monetary policy: a global-model perspective,* Macroeconomic Dynamics, v. 25, 5, pp. 1267-1287, **WP 1156 (December 2017).**

DE PHILIPPIS M., *Multitask agents and incentives: the case of teaching and research for university professors,* Economic Journal, v. 131, 636, pp. 1643-1681, **WP 1042 (December 2015).**

DEL PRETE S. and M. L. STEFANI, *Women as "Gold Dust": gender diversity in top boards and the performance of Italian banks,* Economic Notes, Monte dei Paschi di Siena, v. 50, 2, e12183, **WP 1014 (June 2015).**

FERRERO G., M. LOBERTO and M. MICCOLI, *The assets' pledgeability channel of unconventional monetary policy,* Economic Inquiry, v. 59, 4, pp. 1547-1568, **WP 1119 (June 2017).**

FIDORA M., C. GIORDANO and M. SCHMITZ, *Real exchange rate misalignments in the Euro Area,* Open Economies Review, v. 32, 1, pp. 71-107, **WP 1162 (January 2018).**

GAMBACORTA L., G. RICOTTI, S. SUNDARESAN and Z. WANG, *Tax effects on bank liability structure,* European Economic Review, v. 138, Article 103820, **WP 1101 (February 2017).**

HERTWECK M., V. LEWIS and S. VILLA, *Going the extra mile: effort by workers and job-seekers,* Journal of Money, Credit and Banking, v. 54, 8, pp. 2099-2127, **WP 1277 (June 2020).**

LI F., A. MERCATANTI, T. MAKINEN and A. SILVESTRINI, *A regression discontinuity design for ordinal running variables: evaluating central bank purchases of corporate bonds,* The Annals of Applied Statistics, v. 15, 1, pp. 304-322, **WP 1213 (March 2019).**

LOSCHIAVO D., *Big-city life (dis)satisfaction? The effect of urban living on subjective well-being,* Journal of Economic Behavior & Organization, vol. 192, pp. 740-764, **WP 1221 (June 2019).**

LOSCHIAVO D., *Household debt and income inequality: evidence from Italian survey data,* Review of Income and Wealth. v. 67, 1, pp. 61-103, **WP 1095 (January 2017).**

METELLI L. and F. NATOLI, *The international transmission of US tax shocks: a proxy-SVAR approach,* IMF Economic Review, v. 69, 2, pp. 325-356, **WP 1223 (June 2019).**

NISPI LANDI V. and A. SCHIAVONE, *The effectiveness of capital controls,* Open Economies Review, v. 32, 1, pp. 183-211, **WP 1200 (November 2018).**

PAPETTI A., *Demographics and the natural real interest rate: historical and projected paths for the Euro Area,* Journal of Economic Dynamics and Control, v. 132, Article 04209, **WP 1306 (November 2020).**

PEREDA FERNANDEZ S., *Copula-based random effects models for clustered data,* Journal of Business & Economic Statistics, v. 39, 2, pp. 575-588, **WP 1092 (January 2017).**

2022

ANDINI M., M. BOLDRINI, E. CIANI, G. DE BLASIO, A. D'IGNAZIO and A. PALADINI, *Machine learning in the service of policy targeting: the case of public credit guarantees,* Journal of Economic Behavior & Organization, v. 198, pp. 434-475, **WP 1206 (February 2019).**

ANGELICO C., J. MARCUCCI, M. MICCOLI and F. QUARTA, *Can we measure inflation expectations using twitter?,* Journal of Econometrics, v. 228, 2, pp. 259-277, **WP 1318 (February 2021).**

BARTOCCI A., A. NOTARPIETRO and M. PISANI, *Covid-19 shock and fiscal-monetary policy mix in a monetary union,* Economic challenges for Europe after the pandemic, Springer Proceedings in Business and Economics, Berlin-Heidelberg, Springer, **WP 1313 (December 2020).**

BOTTERO M., C. MINOIU, J. PEYDRÒ, A. POLO, A. PRESBITERO and E. SETTE, *Expansionary yet different: credit supply and real effects of negative interest rate policy,* Journal of Financial Economics, v. 146, 2, pp. 754-778, **WP 1269 (March 2020).**

BRONZINI R., A. D'IGNAZIO and D. REVELLI, *Financial structure and bank relationships of Italian multinational firms,* Journal of Multinational Financial Management , v. 66, Article 100762, **WP 1326 (March 2021).**

CANTELMO A., *Rare disasters, the natural interest rate and monetary policy,* Oxford Bulletin of Economics and Statistics, v. 84, 3, pp. 473-496, **WP 1309 (December 2020).**

CARRIERO A., F. CORSELLO and M. MARCELLINO, *The global component of inflation volatility,* Journal of Applied Econometrics, v. 37, 4, pp. 700-721, **WP 1170 (May 2018).**

CIAPANNA E. and G. ROVIGATTI, *The grocery trolley race in times of Covid-19. Evidence from Italy,* Italian Economic Journal / Rivista italiana degli economisti, v. 8, 2, pp. 471-498, **WP 1341 (June 2021).**

CONTI A. M., A. NOBILI and F. M. SIGNORETTI, *Bank capital requirement shocks: a narrative perspective,* European Economic Review, v.151, Article 104254, **WP 1199 (November 2018).**

FAIELLA I. and A. MISTRETTA, *The net zero challenge for firms' competitiveness,* Envnmental & Resource Economics, v. 83, pp. 85-113, **WP 1259 (February 2020).**

FERRIANI F. and G. VERONESE, *Hedging and investment trade-offs in the U.S. oil industry,* Energy Economics, v. 106, Article 105736, **WP 1211 (March 2019).**

GUISO L., A. POZZI, A. TSOY, L. GAMBACORTA and P. E. MISTRULLI, *The cost of steering in financial markets: evidence from the mortgage market,* Journal of Financial Economics, v.143, 3, pp. 1209-1226, **WP 1252 (December 2019).**

LAMORGESE A. and D. PELLEGRINO, *Loss aversion in housing appraisal: evidence from Italian homeowners,* Journal of Housing Economics, v. 56, Article 101826, **WP 1248 (November 2019).**

LI F., T. MÄKINEN, A. MERCATANTI and A. SILVESTRINI, *Causal analysis of central bank holdings of corporate bonds under interference,* Economic Modelling, v.113, Article 105873, **WP 1300 (November 2020).**

LOBERTO M, A. LUCIANI and M. PANGALLO, *What do online listings tell us about the housing market?,* International Journal of Central Banking, v. 18, 4, pp. 325-377, **WP 1171 (April 2018).**

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MOCETTI S., G. ROMA and E. RUBOLINO, *Knocking on parents' doors: regulation and intergenerational mobility,* Journal of Human Resources, v. 57, 2, pp. 525-554, **WP 1182 (July 2018).**

PERICOLI M. and M. TABOGA, *Nearly exact Bayesian estimation of non-linear no-arbitrage term-structure models,* Journal of Financial Econometrics, v. 20, 5, pp. 807-838, **WP 1189 (September 2018).**

ROSSI P. and D. SCALISE, *Financial development and growth in European regions,* Journal of Regional Science, v. 62, 2, pp. 389-411, **WP 1246 (November 2019).**

SCHIVARDI F., E. SETTE and G. TABELLINI, *Credit misallocation during the European financial crisis,* Economic Journal, v. 132, 641, pp. 391-423, **WP 1139 (September 2017).**

TABOGA M., *Cross-country differences in the size of venture capital financing rounds: a machine learning approach,* Empirical Economics, v. 62, 3, pp. 991-1012, **WP 1243 (November 2019).**

2023

APRIGLIANO V., S. EMILIOZZI, G. GUAITOLI, A. LUCIANI, J. MARCUCCI and L. MONTEFORTE, *The power of text-based indicators in forecasting Italian economic activity,* International Journal of Forecasting, v. 39, 2, pp. 791-808, **WP 1321 (March 2021).**

BARTOCCI A., A. NOTARPIETRO and M. PISANI, *Non-standard monetary policy measures in non-normal times,* International Finance, v. 26, 1, pp. 19-35, **WP 1251 (November 2019).**

DI ADDARIO S., P. KLINE, R. SAGGIO and M. SØLVSTEN, *It ain't where you're from, it's where you're at: hiring origins, firm heterogeneity, and Wages,* Journal of Econometrics,v. 233, 2, pp. 340-374, **WP 1374 (June 2022).**

FERRIANI F., *Issuing bonds during the Covid-19 pandemic: was there an ESG premium?,* International Review of Financial Analysis, v. 88, Article 102653, **WP 1392 (November 2022).**

LILLA F., *Volatility bursts: a discrete-time option model with multiple volatility components,* Journal of Financial Econometrics, v. 21, 3, pp. 678-713, **WP 1336 (June 2021).**

LOBERTO M., *Foreclosures and house prices,* Italian Economic Journal / Rivista italiana degli economisti, , v. 9, 1, pp. 397-424, **WP 1325 (March 2021).**

NERI S., *Long-term inflation expectations and monetary policy in the Euro Area before the pandemic*, European Economic Review, v. 154, Article 104426, **WP 1357 (December 2021).**

ORAME A., *Bank lending and the European debt crisis: evidence from a new survey*, International Journal of Central Banking, v. 19, 1, pp. 243-300, **WP 1279 (June 2020).**

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CIAPANNA E, S. MOCETTI and A. NOTARPIETRO, *The macroeconomic effects of structural reforms: an empirical and model-based approach,* Economic Policy, **WP 1303 (November 2022).**

GIORDANO C., *Revisiting the real exchange rate misalignment-economic growth nexus via the across-sector misallocation channel,* Review of International Economics, **WP 1385 (October 2022).**

FERRARI A. and V. NISPI LANDI, *Whatever it takes to save the planet? Central banks and unconventional green policy,* Macroeconomic Dynamics, **WP 1320 (February 2021).**

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LOMBARDI M. J., M. RIGGI and E. VIVIANO, *Bargaining power and the Phillips curve: a micro-macro analysis, and wages,* Journal of the European Economic Association, **WP 1302 (November 2020).**

RAINONE E., *Real-time identification and high frequency analysis of deposits outflows,* Journal of Financial Econometrics, **WP 1319 (February 2021).**

RIZZICA L., G. ROMA and G. ROVIGATTI, *The effects of shop opening hours deregulation: evidence from Italy,* The Journal of Law and Economics, **WP 1281 (June 2020).**