Value and Momentum Leftovers*

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Abstract

Historically, investing in value and momentum strategies has delivered high excess returns across geographical locations and asset classes. However, no pricing kernel has yet been proposed that fully explains these excess returns, meaning that some alpha remains unexplained — the "leftovers". We find that a pricing kernel comprising nine latent factors extracted from the combined value and momentum cross-section, rather than from the two separate cross-sections, yields no leftovers and achieves a higher Sharpe ratio. Accounting for these leftovers is also key to obtain robust estimates of the risk premia of macro-financial risks priced in the value and momentum cross-section.

Keywords: Value; momentum; pricing kernel; latent factor models.
JEL codes: G12; G15.

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I Introduction

For nearly a century, value investing — the idea of buying undervalued assets and selling overvalued assets — has been part of the backbone of the asset management industry, at least since Graham and Dodd (1934). Another piece of the backbone is momentum investing — the idea of buying assets that have recently performed well and selling assets that have recently performed poorly — which dates back much earlier, to pre-Victorian times.[1] While these ideas were originally validated in the finance literature for US stocks, the subsequent literature has found value and momentum strategies to be profitable both in other stock markets and other asset classes. However, it is now well known that suitably combining value and momentum across international equity markets and across different asset markets provides a markedly superior asset allocation strategy than investing in either a single strategy or a single asset class. This is a central point convincingly documented in an influential paper by Asness, Moskowitz and Pedersen (2013, AMP hereafter).[2]

The empirical evidence by AMP shows clearly that, while value strategies tend to be positively, albeit imperfectly, correlated across different stock markets around the world and across different asset markets (such as currencies, bonds and commodities), and the same occurs for momentum strategies, value and momentum strategy excess returns are systematically and strongly negatively correlated with each other. This negative correlation provides large diversification benefits, thereby leading to much higher risk-adjusted excess returns (Sharpe ratios) with even a naïve 50/50 combination of value and momentum strategies. The excess returns

[1] Chabot, Gysels and Jagannathan (2024) trace back early references to momentum investing to David Ricardo's writings and his own investments. Academic research documenting formally that in the US equity market value stocks outperform growth stocks starts with Stattman (1980), Rosenberg, Reid and Lanstein (1985) and Fama and French (1992). The momentum literature starts with Jegadeesh and Titman (1993) and Asness (1994).

[2] Value returns have been documented internationally in various asset classes: individual stocks (Fama and French, 1998; Liew and Vassalou, 2000; Campbell, Giglio and Polk, 2025), equity indices (Asness, Liew and Stevens, 1997), government bonds (Asness et al., 2013; Brooks and Moskowitz, 2021), currencies (Asness et al., 2013; Menkhoff, Sarno, Schmeling and Schrimpf, 2017), and commodities (Asness et al., 2013). Momentum returns are also globally prevalent across asset classes: individual stocks (Rouwenhorst, 1998; Liew and Vassalou, 2000; Griffin, Ji and Martin, 2003), equities indices (Chan, Hameed and Tong, 2000; Bhojraj and Swaminathan, 2006), government bonds (Asness et al., 2013; Sihvonen, 2024), currencies (Menkhoff, Sarno, Schmeling and Schrimpf, 2012b), and commodities (Erb and Harvey, 2006; Miffre and Rallis, 2007; Shen, Szakmary and Sharma, 2007; Gorton, Hayashi and Rouwenhorst, 2013). Value and momentum have been examined jointly in a number studies. Blitz and Van Vliet (2008) was one of the first studies to document the large diversification benefits of combining value and momentum strategies internationally. Fama and French (2012) show that value and momentum returns are prevalent across a number of stock markets. Naturally, AMP made a lasting contribution to the literature by displaying the prevalence of value and momentum returns across a breadth of asset classes and markets, and the importance of combining value and momentum strategies for diversification. More recently, Polk, Vayanos and Woolley (2022) provide theory and empirical evidence to explain how both value and momentum strategies can generate high Sharpe ratios and display a negative correlation from the perspective of a long-horizon investor.

from such a broad cross-section of (48) value and momentum portfolios is not priced by benchmark asset pricing models in the literature. Thus AMP propose a purpose-built pricing kernel (or stochastic discount factor, SDF) in the form of a reduced-form three-factor model comprising a world equity market factor and two global ("everywhere") value and momentum factors, which is shown to perform much better than any benchmark model considered. However, even this three-factor model cannot fully price this demanding cross-section of value and momentum portfolios, so that some alpha remains as a "leftover". The same conclusion is reached in subsequent research aimed at pricing this cross section of assets (e.g., Cooper, Mitrache and Priestley, 2022). In this sense, no pricing kernel has yet been proposed that fully prices these portfolio excess returns.

In this paper, we revisit the pricing kernel of the cross-section of 48 value and momentum portfolios used by AMP with the benefit of an updated sample of data that includes more than 10 additional years.[3] The updated sample reveals two important facts. First, the alpha leftover that is unexplained by both conventional asset pricing models and the three-factor model of AMP remains statistically and economically significant, meaning that the quest for an appropriate pricing kernel remains a central question in this research agenda. Second, the performance of the 50/50 combination of value and momentum portfolios has deteriorated sharply over the updated sample period. These two points are illustrated in Figure 1 and Figure 2.

[Figure 1 about here.]

[Figure 2 about here.]

In Figure 1, we plot the actual average returns of the 48 value and momentum portfolios against the model-implied expected returns using the three-factor pricing model of AMP, both for the full sample we employ in the empirical analysis (1983-2023) and for the sample starting after 20 years (2003-2023).[4] The results indicate that, over both the full sample and the post-20 year sample, the model performs reasonably well with an R^2 of at least 66%. However, for both sample periods, the average absolute alpha unexplained by the model amounts to more than

[3] We are very grateful to the authors for kindly providing us with updated data for the 48 portfolios and the factors used in the pricing kernel of AMP.

[4] The sample employed by AMP actually begins in 1973 but we employ here data from 1983 in order to have a balanced panel of data throughout. Therefore, the subsample of 20 years for 2003-2023 is about half of the full sample we use. Moreover, in Figure IA.1 in the Internet Appendix, we show that the AMP model also outperforms other conventional asset pricing models in the updated sample.

1.60% (annualized), and the null hypothesis that the alphas are jointly zero is strongly rejected on the basis of the GRS test (Gibbons, Ross and Shanken, 1989). The graph in Figure 2 shows the Sharpe ratio, computed both recursively and over a 3-year rolling window, for the 50/50 combination strategy. The dotted vertical lines indicate July 2003 (about half of the sample) and July 2011, when the sample of AMP ends. The Sharpe ratio from the strategy would have been 1.71 in the first half of the sample, and 1.46 using data up to 2011, which is very close to the Sharpe ratio of 1.45 reported by AMP. It is also clear that there is a strong downward trend in the Sharpe ratio, which converges to 1.10 at the end of the sample; in fact the Sharpe ratios in the second part of the sample (2003-2023) and post-publication (2011-2023) are modest, 0.44 and 0.21 respectively. Taken together, these results indicate that the performance of the 50/50 combination has deteriorated sharply over the 12 years after 2011, while the cross-sectional alpha unexplained by the three-factor model is a fairly constant feature throughout the sample.[5]

The above findings raise important questions, and we address the following ones in this paper. First, how many (and which) factors should the optimal pricing kernel comprise to fully price the joint cross-section of value and momentum portfolio returns? Second, does the tangency portfolio implied by such optimal pricing kernel generate strong investment performance throughout the sample and out-of-sample? Third, which observable (tradable or non-tradable) factors, from a wide range of factors proposed in the asset pricing literature, drive the pricing kernel?

We address these questions leveraging on important advances made in asset pricing methodology in recent years. Historically, empirical asset pricing analysis has relied on pricing kernels, either motivated by theory or (mostly) in reduced form, which are inherently subject to omitted-variable and measurement-error problems. Giglio and Xiu (2021) propose a three-pass procedure that addresses both issues. The procedure 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. Thus the method relies first on estimating the latent factors, and

[5] A recent paper by Cooper et al. (2022) studies whether the cross-section of value and momentum portfolio excess returns can be understood as compensation for global macroeconomic risk. They propose a factor model comprising five global macroeconomic risk factors, which are global variants of the factors used by Chen, Roll and Ross (1986) and in the style of the factors used by Griffin et al. (2003) to price momentum globally. Their evidence shows that this pricing kernel can capture the positive return premia of value and momentum while at the same time implying a negative correlation of the value and momentum return premia and the fact that an equal-weighted combination strategy earns a positive average return. In Figure IA.2 in the Internet Appendix, we show that even this pricing kernel cannot fully price the broad cross-section of value and momentum portfolios everywhere, and a statistically and economically significant alpha remains unexplained. We will make use of the macro risk factors used in this model later in the paper and thank the authors for sharing these data with us.

then on determining the factor structure of the optimal SDF. While Giglio and Xiu (2021) use principal component analysis (PCA), we employ the Risk Premium Principal Component Analysis (RP-PCA) method of Lettau and Pelger (2020a,b). 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 premia (Sharpe ratios) can be detected more easily.[6] The three-pass procedure using RP-PCA to extract the latent factors not only allows to pin down the optimal pricing kernel (number of latent factors) required to fully price a cross-section of test asset returns, but also to obtain estimates of the risk premium for any candidate risk factor (tradable or non-tradable) that are robust to omitted-variable and measurement-error biases. In practice, this procedure projects the candidate factors onto the space spanned by the selected latent factors. The factors' risk-premium estimates are then given simply by linear combinations of the prices of risk of the latent factors. In this way, one can remain agnostic about the set of "true" risk factors, and yet obtain robust estimates of factors' risk premia.

Applying this three-pass procedure to the panel of 48 value and momentum portfolio excess returns, a number of interesting findings emerge that help shed light on (a) the optimal latent-factor SDF, (b) the performance of the investment strategies that combine value and momentum signals, and (c) the macro-financial sources of the risk that drive the resulting excess returns. We present the findings in this order. First, we show that the SDF requires nine factors to price fully the joint cross-section of value and momentum test asset returns and maximize the Sharpe ratio of the tangency portfolio implied by the SDF. Five of these nine factors are pricing factors, as they display statistically significant average excess returns and high Sharpe ratios, and hence enter the SDF with large weights. Four of the factors are time series factors with insignificant risk premia, but they enter the latent-factor model as they explain a sizable part of the systematic variance of the test asset returns.[7] These results suggest that, despite the

[6] This combined procedure that uses the methods developed separately by Giglio and Xiu (2021) and Lettau and Pelger (2020a,b) is referred to as the "augmented three-pass method", and it has been shown that the use of RP-PCA enhances the three-pass model pricing performance. See, for example, Nucera, Sarno and Zinna (2024).

[7] It is useful to note that RP-PCA empirically performs better than PCA in this analysis in extracting a parsimonious set of factors that price the test assets. In fact, using PCA, the number of latent factors required to eliminate any alpha would be in excess of 20. We also find 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. Our baseline RP-weight is 20 in the core results of the paper.

existence of a strong factor structure for both value and momentum portfolios, a fairly rich model is required to explain the cross-sectional differences in the average excess returns of these test assets.

Importantly, the three 'everywhere' AMP factors are unable to subsume several of these latent factors and price the tangency portfolio's excess returns, particularly in the second half of the sample period. Specifically, the AMP factors cannot fully explain the information in the latent factor model if it includes more than three factors. This is because latent factors four, seven, eight and nine are high-risk-premium factors, which exhibit residual alphas when regressed onto the AMP factors. Since the optimal latent factor model fully prices the cross-section of value and momentum portfolio excess returns, these residual alphas are closely related to those left unexplained by the AMP model in the cross-section of value and momentum portfolio excess returns. Thus, we use the term 'leftovers' interchangeably for these two types of residual alpha – i.e. the alpha in the cross-section unexplained by the AMP model, and the components of the latent factors that are unexplained by the AMP factors.

Second, the Sharpe ratio of the tangency portfolio (with mean–variance weights) implied by the nine-factor model SDF is 1.47 over the full sample of data, 1983-2023. Recursive estimation of the SDF shows that the factor structure is quite stable over time, although the eight and nine factors become particularly important in the last five years of the sample. Using an initial window of 20 years and estimating the nine-factor SDF for the remaining 20 years in an out-of-sample setting generates a Sharpe ratio of 1.07 over the period 2003-2023. Considering that the in-sample Sharpe ratio over the 2003-2023 period is 1.40, this result suggests that, while there is some deterioration in the performance when we move the analysis out-of-sample, the performance of our proposed model remains strong also in the latter part of the sample. This is due to the richer characterization of the SDF that models value and momentum jointly from the outset, hence exploiting the full covariance of value and momentum portfolios via the optimal latent factor structure.

To understand better the drivers of the superior performance of the latent-factor SDF, we decompose the Sharpe ratio of the optimal tangency portfolio into two key components: (i) the Sharpe ratio attributable to the combination of value and momentum "factors" extracted from *separate* cross-sections of test assets (the *spanned* component), and (ii) a residual orthogonal component, which is not captured by forming factors from independent cross-sections — in the traditional asset pricing fashion — but rather by exploiting the full cross-section of value and momentum excess returns (the *unspanned* component). Specifically, we first form two SDFs, one for value and one for momentum, applying RP-PCA to the two cross-sections of 24 test assets, separately. This gives us two distinct latent-factor SDFs and two tangency portfolios for value and momentum. Then, we combine the two value and momentum tangency portfolios, using mean–variance weights. Interestingly, the mean–variance weights turn out to be 0.48 and 0.52, meaning that the 50/50 combo is not far from being optimal. The resulting tangency portfolio has a Sharpe ratio of 1.18 (val/mom), which is much lower than the Sharpe ratio of 1.47 obtained when modeling the joint cross-section of 48 test assets (val&mom), indicating that part of the performance of our optimal latent-factor SDF and tangency portfolio stems from being able to combine freely the value and momentum portfolios. We design a simple decomposition of the tangency portfolio excess returns that allows us to recover the Sharpe ratio contributions of (i) and (ii), as defined above. From this decomposition, we find that the Sharpe ratio attributable to spanned component is 0.96, which explains about two thirds of the Sharpe ratio of the optimal tangency portfolio. As a result, the unspanned component accounts for the remaining 0.51 of the total Sharpe ratio. Hence, just over one third of the Sharpe ratio stems from the unspanned component, which cannot be captured by considering investment strategies and constructing pricing factors in isolation. The bottom line is that, in general, it is suboptimal to construct factors from individual strategies or asset classes and then combine them into a model to price the joint cross-section, as this leads to a loss of information. The improvement of the efficient frontier obtained by freely combining value and momentum portfolios across both strategies and asset classes/markets is economically large.[8]

Third, in the final part of the paper, using the third-pass of the Giglio and Xiu (2021) method, we estimate the risk premia of a large number of candidate factors (tradable and non-tradable) to shed light on the macro-financial sources of risk through the lens of the optimal latent factor SDF. We find that several sources of macro-financial risks are priced into the cross-section of value and momentum portfolios and some of these macro-financial factors have high (absolute) risk premia and Sharpe ratios. Importantly, we demonstrate that accurate estimates of these premia require the SDF to fully span the cross-section of test assets.

[8]This key empirical finding is further corroborated by simulations designed to quantify the Sharpe ratio contribution that is attributable to the unspanned component under a data generating process (DGP) calibrated on our data. Specifically, we document how, if the true DGP for the SDF is a high-dimensional latent factor model of the kind proposed in our paper, separating value and momentum strategies and combining them ex post leads to a large loss of information. This induces a reduction in the Sharpe ratio, on average across 10,000 simulations, of about 31% relative to the Sharpe ratio attainable when estimating the factors from the joint cross-section of value and momentum returns.

Indeed, while many macro-financial factors relate to the level of the SDF, the premia of some candidate macro-financial factors change significantly when moving to larger latent factor models. This highlights the importance of accounting for 'leftovers', as failing to do so can lead to an inaccurate characterization of the risk-return trade-off. For example, the risk premia of some candidate factors, such as interest rates, mainly derive from their exposure to parts of the optimal SDF not captured by AMP factors — the 'leftovers'.

Using the three-pass method, we also show that the spanned (R_S) and unspanned (R_U) components that drive the optimal tangency portfolio excess returns (R_{VM}) behave very differently, for several reasons. First, this is because they are connected to different parts of the SDF, or to the same parts but with very different exposures. For instance, the risk premium of the spanned component R_S is primarily influenced by the first seven latent factors, whereas that of the unspanned component R_U is predominantly affected by its exposure to latent factors eight and nine. These two latent factors are indeed largely irrelevant for the value (R_V) and momentum (R_M) tangency portfolios' excess returns extracted from the two separate cross-sections. This suggests that the importance of the leftovers mainly emerges when value and momentum portfolios (rather than value and momentum factors) are combined freely. We then find that the only other economically relevant source of procyclical risk for R_U is factor four, which is also a procyclical source of risk for momentum and countercyclical for value. This factor indeed seems to capture the extensively documented negative correlation of value and momentum, which we can relate to several sources of macro-financial risk. Furthermore, R_U has a negative loading on the level of the SDF, whereas R_S is highly positively exposed, which explains why the optimal tangency portfolio R_{VM} is less exposed to that part of the SDF than its spanned component.

By performing simple univariate spanning regressions of the tangency portfolio excess returns and its components on a large number of factors, we find that the priced macro-financial risk factors are primarily related to the spanned component of the tangency portfolio. Indeed, while R_S is exposed to all the priced macro-financial risk factors, R_U is exposed to only a subset. Furthermore, the macro-financial exposures of R_U often have opposite signs to the R_S exposures, suggesting that R_U can hedge some of the macro-financial risks to which R_S is exposed (e.g. intermediary leverage). However, R_U and R_S have similar exposures to certain high-risk-premium macro-financial factors, such as those relating to US interest rates and monetary policy surprises. This indicates that R_U's positive risk premium is also consistent with a risk-based explanation. Finally, all univariate regressions yield large, statistically significant intercepts, implying that neither the tangency portfolio nor any of its components can be fully explained by a single source of macro-financial risk. Nevertheless, we show which subset of macro-financial factors, selected using LASSO, can explain the returns of the optimal tangency portfolio. These include factors related to interest rates, volatility, hedge fund trend-following strategies in equities and commodities, sentiment, and the global financial cycle.

The paper proceeds as follows. Section II presents the primary econometric methods used. These are (i) the RP-PCA of Lettau and Pelger (2020a,b), used to recover the optimal latent-factor pricing kernel from the value and momentum test assets, and (ii) the three-pass method of Giglio and Xiu (2021), employed to assess the priced sources of macro-financial risks in the cross-section of test assets. Section III introduces the value and momentum portfolios and factors of AMP, and the candidate macro-financial risk factors. Section IV presents the main empirical results, including the different parts of the value and momentum SDF and the estimates of the risk premia of the candidate macro-financial factors. Section V concludes.

II Asset Pricing Methods

In this section, we first describe the RP-PCA method proposed by Lettau and Pelger (2020a,b, LP hereafter), which is used to extract the latent factors from the cross-section of value and momentum test assets and determine the optimal SDF. We also discuss the set of evaluation criteria we rely upon to identify the relevant latent factors that enter the SDF. We then briefly discuss the three-pass method of Giglio and Xiu (2021, GX hereafter). We differ from GX in that we use latent factors estimated by RP-PCA rather than by PCA. Thus, we rely on the augmented three-pass method, recently employed by Nucera et al. (2024, NSZ hereafter), which combines LP's RP-PCA method with GX's three-pass method. This framework allows us to identify the optimal latent factor SDF that spans the information in the joint cross-section of value and momentum portfolio returns. Later this method also allows us obtain robust estimates of candidate factor risk premia in the sense that the estimates are free from both measurement-error and omitted-variable biases.

II.A Optimal Pricing Kernel

Latent Factor Extraction. Assume K latent factors capture the systematic component of asset returns and the unexplained idiosyncratic component subsumes the asset-specific risks, such that

$$\underbrace{X}_{T\times N} = \underbrace{F}_{T\times K}\underbrace{\psi^\top}_{K\times N} + \underbrace{\epsilon}_{T\times N}, \tag{1}$$

where X denotes the excess returns of the test assets, F is the matrix of latent factors, ψ are the factor loadings, and ϵ are the idiosyncratic components of the asset returns. If the factors and residuals are uncorrelated, the covariance matrix of the returns is given by

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

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

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

where $\overline{X}$ is the sample mean of the excess returns. The estimated factor loadings, $\widehat{\psi}$, are proportional to the eigenvectors associated with the largest eigenvalues of Σ_{PCA}. The factors $\widehat{F}_t$ are then obtained by regressing the asset returns on the factor loadings.

LP instead develop RP-PCA, which is tantamount to applying PCA to

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

where ω is the RP-weight. Using a strictly positive RP-weight, the estimated latent factors reflect the information in both the first and second moments of excess returns.[9] Specifically, RP-PCA jointly minimizes the unexplained time-series variation and the cross-sectional pricing errors

$$\min_{F,\psi}\left\{\underbrace{\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{nt} - F_t\psi_n^\top)^2}_{\text{TS: unexplained variation}} + \omega\underbrace{\frac{1}{N}\sum_{i=1}^{N}(\overline{X}_n - \overline{F}\psi_n^\top)^2}_{\text{CS: pricing error}}\right\}, \tag{5}$$

where $\overline{F}$ is the vector of latent factor expected values. Thus, RP-PCA with $\omega > 0$ combines two moment conditions, so that the estimated factor loadings, $\widehat{\psi}$, are now proportional to the

[9]PCA imposes $\omega = -1$ and thus only considers the information in the second moments, neglecting that in the first moments.

eigenvectors associated with the largest eigenvalues of the Σ_{RP} matrix. In this way, RP-PCA leads to a generalized notion of *signal-to-noise ratios*, where the signal also embeds information about expected returns, which is key in any asset pricing model. RP-PCA should make it easier to detect weak factors with high Sharpe ratios, as the weak signal in their variances is enhanced by the information in their means. At the same time, it should prevent the selection of spurious factors, as the estimated factors must explain a substantial proportion of the time-series variation. As a result, RP-PCA should help estimate relevant asset pricing factors more efficiently than PCA. This is important in order to identify all relevant asset pricing factors, so that there is no alpha leftover in the cross-section of value and momentum portfolio returns.

Latent Factor Selection. RP-PCA provides estimates of the latent factors. We employ multiple evaluation criteria to select the K factors that should be included in the optimal SDF as well as the appropriate RP-weight. While assessing latent factor statistics, such as their risk premia and Sharpe ratios, is informative in distinguishing time-series from pricing factors, other metrics are particularly useful in assessing the properties of the SDF, leading to a more comprehensive evaluation.[10] First, it is common to assess how the Sharpe ratio of the tangency portfolio of the mean–variance frontier spanned by a linear combination of the latent factors evolves as one varies the number of factors. Specifically, the tangency portfolio is given by $\pi(F) = \widehat{F} \times \widehat{b}_{MV}^{\top}$, where $\widehat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$ is a 1 $\times$ K vector capturing the factor weights in the SDF, $\varphi_t = 1 - (\widehat{F}_t - \mu_F)\widehat{b}_{MV}^{\top}$. Thus, we consider the Sharpe ratios of $\pi(\widehat{F}_{1-k})$ for k = 1, ..., K. This metric allows us to examine the marginal increase in the Sharpe ratio as one adds latent factors in the SDF sequentially. Second, we rely on the idiosyncratic variance ($\overline{\sigma}_{\epsilon}^2$) and root-mean-square error ($\overline{RMS}_{\alpha}$) statistics, which are easily obtained from ordinary least squares (OLS) time-series regressions

$$X_{nt} = \alpha_n + \widehat{F}_t B_n^{\top} + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{6}$$

where the intercept α_n captures the magnitude of the asset-specific pricing errors.[11] Then, it

[10] Individual factors are not identified because they are not rotation invariant, while the multi-factor SDF and the tangency portfolios are. Specifically, we follow LP and normalize the loadings so that the factors are orthogonal with each other. To do this, we use the Gram-Schmidt method, as it has the advantage of orthogonalizing the factors sequentially. The models based on the original and orthogonal factors are observationally equivalent. The factors are orthogonalized mainly to facilitate their economic interpretation, e.g., regarding their different contributions to the SDF.

[11] Note that Equation (6) is essentially the OLS counterpart of the factor model of Equation (1). The two differ in that the OLS model includes a constant and does not correct for the RP-weight (see, e.g., Nucera et al. (2024)). However, LP argue that these differences are typically negligible in the data.

follows that $\overline{RMS}_\alpha = \sqrt{\widehat{\alpha}\widehat{\alpha}^\top/N}$, and $\overline{\sigma}^2_\epsilon = \frac{1}{N}\sum_{n=1}^N [Var(\widehat{\epsilon}_n)/Var(X_n)]$. These statistics are particularly useful for evaluating the trade-offs associated with the choice of the RP-weight, ω. This is because, ceteris paribus, a higher weight on expected returns should lead to smaller pricing errors, but at the cost of higher idiosyncratic variance. That is, in theory, there is a trade-off such that ω should move pricing errors and explained systematic variance in opposite directions. While these statistics are obtained from the first pass, other statistics can be constructed from the second pass of the Fama and MacBeth (1973) procedure. Thus, third, we use the Mean Absolute Errors (MAE) and R^2s derived from the second pass to shed light on the cross-sectional fit of the model.

For our purposes, the ability of the model to span the cross-section of test assets is critical. The standard approach would be to select the most parsimonious model which eliminates all alphas, on average. However, tests of this sort — such as that of Gibbons et al. (1989) — are based on the assumption that N is fixed and $T \to \infty$, whereas 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 standard GRS-type tests are biased even in large samples (see Lettau and Pelger, 2020b).

Therefore, we use a simple and yet robust multiple-testing approach. Specifically, we perform N tests of the null hypothesis $\mathcal{H}0$: $\bar{\epsilon}_n = 0$ for $n = 1, \ldots, N$, to determine how many assets have significant average pricing errors, as the dimensionality of the SDF varies. To test the statistical significance of each of the alphas, we employ a wild bootstrap procedure, similar to Giglio, Liao and Xiu (2021, GLX). We perform the tests at the 5% confidence level, but also at more stringent levels (e.g., employing the Benjamini and Hochberg (1995) correction, as in GLX). In doing so, we provide an appropriate adjustment for multiple-hypothesis testing bias (see Section IA.2.3 of the Internet Appendix for a detailed description of the bootstrap and the multiple-hypothesis testing bias correction). We also use the same bootstrap to assess the significance of the MAEs.

Summing up, we look at these different metrics together in an attempt to select the best performing model for pricing the cross-section of test assets. Having established the optimal latent-factor SDF, we can then turn to GX's three-pass estimation method. This method allows us to achieve robust estimates of the risk premia of a long list of tradable and non-tradable candidate factors, shedding light on the sources of macro-financial risk priced into the cross-section of value and momentum test assets.

II.B Three-pass Estimation

Below we briefly outline the three-pass procedure. We repeat the first two passes mainly for convenience, as they are already subsumed by the RP-PCA latent factor extraction and selection described earlier. Indeed, the first pass consists of estimating test asset risk exposures to the latent factors via time-series OLS regressions. However, LP show that in order to retrieve the RP-PCA risk exposures, one needs to transform the data such that

$$\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{7}$$

where $\tilde{X}_{nt} = X_{nt} + \tilde{\omega}\bar{X}_{nt}$, and the vector $\tilde{F}_t$ contains elements defined as $\tilde{F}_{kt} = \widehat{F}_{kt} + \tilde{\omega}\bar{F}_{kt}$ for $k = 1, \ldots, K$, with $\tilde{\omega} = \sqrt{\omega + 1} - 1$. Thus, the OLS regressions are slightly different from those in GX: in fact, with PCA ($\omega = -1$), the data are not transformed. The second pass provides estimates of the latent factor prices of risk, by running a cross-sectional regression of average realized excess returns on the estimated exposures similar to the classic Fama-MacBeth procedure

$$\overline{X}_n = \widehat{\psi}_n \gamma^\top + a_n, \quad n = 1, \ldots, N, \tag{8}$$

where γ is the $1 \times K$ vector of the latent factor prices of risk. Since the factors extracted using the RP-PCA method are return-based with unrestricted means, in the absence of arbitrage the factor prices of risk are simply equal to their means (i.e., $\gamma = \mu_F$). However, this second pass is still useful for evaluating the model pricing ability, as illustrated above, and for determining the asymptotic standard errors of the candidate factor risk premia.

Then, in the third pass, the exposures and risk prices of any candidate factor, say g_t can be estimated. These estimates are obtained sequentially, first by running a time-series spanning regression of the candidate factor innovation, g_t^ι, on the de-meaned latent factors, $\widehat{F}_t^\iota = \widehat{F}_t - \mu_F$:

$$g_t^\iota = \widehat{F}_t^\iota \eta^\top + u_t, \tag{9}$$

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 loadings, one implements

$$\widehat{\lambda}_g = \widehat{\gamma}\widehat{\eta}^\top, \tag{10a}$$

$$\widehat{g}_t = \widehat{F}_t \widehat{\eta}^\top, \tag{10b}$$

and obtains the *price of risk* of the candidate factor, $\widehat{\lambda}_g$, and the *de-noised* candidate factor, $\widehat{g}_t$. The resulting *de-noised* factor is return-based and free of measurement error and unpriced risk.

III Data

Value and Momentum Everywhere (VME). The VME data are AMP's updated test assets and corresponding risk factors.[12] The VME portfolios, or test assets, are constructed as long-only terciles for both value and momentum across eight markets/asset classes. The resulting 48 portfolios are thus equally split between value and momentum. The four markets cover individual stocks in the US, the UK, Continental Europe and Japan, while the four asset classes cover equity index futures, government bonds, currencies, and commodity futures.[13] Specifically, within each market/asset class, securities are sorted into three portfolios according to either their value or momentum signals — low (P1), medium (P2), and high (P3). AMP refer to the resulting 24 portfolios from the four stock markets as Security Selection (SS) portfolios, and the 24 portfolios from the four asset classes as Asset Allocation (AA) portfolios. In total, three portfolios for the two strategies in each of the eight asset classes gives $N = 2 \times 3 \times 8 = 48$ test assets. The VME data are available at monthly frequency and start in 1973. However, the panel is not balanced prior to July 1983, so we work with the sample from July 1983 to December 2023.

The VME dataset also includes two types of long-short risk factors: (i) high-minus-low (HML) spread portfolios, and (ii) rank spread portfolios. The latter are formed by weighting securities in proportion to their cross-sectional rank, appropriately scaled so that the overall portfolio is one dollar long and one dollar short. Rank factors should therefore limit the impact of outliers, as they trade all securities and not just those in the corner portfolios, as is instead the case with popular HML factors. In their three-factor model, AMP construct the global value and momentum factors from the respective cross-sectional rank factors in two steps, as follows. First, the individual value and momentum rank factors are aggregated at the market/asset class level, scaling each factor by the inverse of its ex-post full sample volatility. As a result, one obtains one SS and one AA factor for value, and similarly the AA and SS factors for momentum. The global value and momentum factors are then obtained by equally weighting the respective

[12] We thank Cliff Asness and AQR for kindly revising and making this data available upon request. We refer to AMP and the AQR website for further details on the construction of the VME data.

[13] Individual stocks are value-weighted by their market capitalization at the beginning of the month, while non-stock asset classes are equally-weighted.

AA and SS factors, again scaled by their full-sample volatilities. In addition to the global value and momentum return factors, the three-factor pricing model of AMP incorporates the excess return on the MSCI World Index.

Tables IA.1 and IA.2 present summary statistics of the test assets and risk factors. For ease of comparison, we follow the format of Tables 1 and 2 in AMP. We find that the properties of the updated data are very similar to those of the data used by AMP ending in 2011. In general, these summary statistics suggest consistent performance of value and momentum for each of the major markets and asset classes examined, although not all factor returns are statistically significant. More importantly, it is clear that the simple 50/50 combination of value and momentum generates substantial improvements in Sharpe ratios due to the robust negative correlation between the excess returns of the two strategies, which ranges from -0.44 (Commodities) to -0.62 (US stocks). Combining the stock and non-stock value and momentum strategies across all asset classes produces the largest Sharpe ratios. In this case, the 50/50 value and momentum combination portfolio produces an annual Sharpe ratio of 1.10 (see also Figure 2). Therefore, the central point of AMP that combining value and momentum strategies across different geographical locations and asset classes substantially enhances risk-adjusted investment performance is apparent. It is, however, worth noting that the Sharpe ratio of 1.10 on the AMP updated sample is about one third lower than the Sharpe ratio of 1.45 reported by AMP, which raises the question whether the performance of this approach after the publication of AMP has deteriorated sharply and, if so, why. We will delve deeper in this analysis later in the paper.

Candidate Risk Factors. We employ additional data for tradable and non-tradable candidate risk factors in the three-pass estimation. These factors are chosen to capture a wide range of economic phenomena with the aim of shedding light on the sources of macro-financial risks priced into the joint cross-section of value and momentum portfolios. The *tradable* factors cover several popular investment strategy returns such as, for example, the 13 themes of Jensen, Kelly and Pedersen (2023), the betting-against beta factor of Frazzini and Pedersen (2014), and the returns of hedge fund trend-following strategies (Fung and Hsieh, 2001). The *non-tradable* factors capture risks from many sources, related to financial uncertainty, liquidity, crash risk, macro, interest rate & monetary policy, political uncertainty, and behavioral features.[14] While

[14]Tradable factors are return-based factors, so their means provide a model-free estimate of their risk premium. Market-based factors which are not expressed in returns — e.g., the MOVE and VIX indices — are treated as non-tradable.

in many cases the distinction between macro-financial factors is not exact as they may relate to sources of risk that are likely to be correlated both conceptually and statistically, we adopt these groupings for convenience of exposition and ease of interpretation. As is common in asset pricing (e.g., Merton 1973), we first convert non-tradable factors into innovations, by simply taking the residuals from an AR(1) process. We provide full details of each of the candidate factors, including definitions, sources, and sample availability, in Table IA.3 of the Internet Appendix.

IV Empirical Analysis

In what follows, we present the main findings of the empirical analysis. In Section IV.A, we determine the optimal pricing kernel, or SDF, over the full sample period. Then, in Section IV.B we assess its stability over time, and investigate the out-of-sample (OOS) performance of the latent factor model, to complement the in-sample (IS) evidence. In Section IV.C, we explore how the latent-factor model compares with the AMP three-factor model, relying on simple spanning regressions. In Section IV.D, we decompose the optimal tangency portfolio returns into various components and identify the value and momentum leftovers. In Section IV.E, we shed light on the macro-financial sources of risk priced in the value and momentum cross-section through the lens of the three-pass method, also highlighting how the components of the tangency portfolio connect with different macro-financial risks. In Section IV.F, using simple penalized regressions, we recover an economically-interpretable reduced-form model to span the optimal latent-factor SDF and its components.

IV.A Optimal Pricing Kernel

First, we implement RP-PCA on the joint cross-section including both the value and momentum portfolios, resulting in 48 test assets. Table 1 presents diagnostics and evaluation criteria described earlier, for the first ten factors extracted with baseline penalization $\omega = 20$.

[Table 1 about here.]

Panel A shows that the latent factors F_1, F_4, F_7, F_8 and F_9 are pricing factors, having statistically significant mean returns, with high Sharpe ratios. As such, these factors generally receive the largest weights in the optimal SDF, having important asset pricing implications. Among these factors, the eighth and seventh factors have the largest weights. The first factor has the smallest weight, as it mostly acts as a level factor and captures time-series variation in the test asset returns. The remaining factors (F_2, F_3, F_5, F_6) are time-series factors as they display statistically insignificant mean returns, low Sharpe ratios, and limited marginal contribution to the maximal Sharpe ratio.[15] However, while these time-series factors have little (if any) cross-sectional pricing power, they capture important time-series properties of the test assets and hence enter the SDF, albeit with small weights (see, e.g., Lewellen, 2023, for a recent exposition on the importance of time-series factors in asset pricing models). For example, the exclusion of such factors can affect the behavior and Sharpe ratios of the de-noised candidate factors in the third pass, as well as the first and second pass pricing criteria. In addition, an important insight from GX, which is also confirmed by the simulations in NSZ, is that it is typically better to include slightly more factors than fewer in that the problems caused by omitted-variable bias in risk premium estimation are more severe than the problems caused by overfitting the SDF. Using a nine-factor model, the Sharpe ratio of the tangency portfolio is 1.47, with factors F_7-F_9 accounting for roughly 0.70. The addition of F_{10} provides a nil marginal contribution to the Sharpe ratio of the tangency portfolio.

Panel B reports outputs from the first two passes of the procedure, as well as the pricing error tests. These pieces of evidence, taken together, further support the choice of a nine-factor model for the SDF. They also clearly show the important contributions of factors seven and eight, and to a lesser extent the improvement achieved by including the ninth factor. Specifically, the first pass shows that both the idiosyncratic variance and the average root-mean-squared pricing error decrease noticeably when the ninth factor is included. This improvement is also evident in the second pass statistics (e.g., the reduction in the cross-sectional pricing errors), although the mean absolute errors are statistically insignificantly different from zero already with the eight-factor model. Consistent with this evidence, when we also perform tests that take into account multiple hypothesis bias, we find that at least the first eight factors are required to fully span the information in the cross-section of test assets and ensure that all 48 individual

[15] Figure IA.3 in the Internet Appendix shows the cumulative returns for each of the first nine latent factors.

pricing errors are statistically insignificant.[16]

[Figure 3 about here.]

The very accurate pricing performance of the nine-factor model is clearly visible from Figure 3, where we plot realized versus model-implied average excess returns for all test assets and for selected SDFs comprising four, seven, eight and nine factors: the pricing errors are indeed small, and there is no tendency for the model to systematically mis-price portfolio returns. In fact, the model-implied average portfolio excess returns are very close to the realized ones. Such pricing accuracy is not achieved by more parsimonious models, such as the four- and seven-factor models. Overall, using $\omega = 20$, the evidence presented suggests that at least an eight-factor model, but most likely a nine-factor model, are required to fully span the joint cross-section of value and momentum test asset returns.

Finally, we note that the RP-weight of 20 is the same penalty value used by LP and NSZ, which also seems an appropriate empirical choice for our sample. Indeed, Table IA.4 in the Internet Appendix reports results for a wide range of ω penalty weights, lending support to this choice. Importantly, standard PCA ($\omega = -1$) appears to perform much worse than RP-PCA, both in terms of the model's pricing ability and maximal Sharpe ratio — a ten-factor model yields Sharpe ratios of 0.76 and 1.47 using $\omega = -1$ and $\omega = 20$, respectively.[17] At the same time, the gain in terms of explained systematic variance is negligible (i.e., the unexplained idiosyncratic variances are essentially the same for the two RP-weights). Thus, similar to LP and NSZ, we find no trade-off in the data, such that the superior performance of RP-PCA over PCA is clear. Moreover, we find no qualitative difference in using a higher RP-weight than 20. Even when using $\omega = 50$, the Sharpe ratio increases only slightly and the pricing errors are very similar.[18]

[16]Inference on the mean absolute and individual pricing errors is based on an adaptation of the wild bootstrap procedure of Giglio et al. (2021) to model estimation via RP-PCA for latent factor models of increasing dimensionality. 2,000 bootstrap simulations are conducted for each latent factor model, F_{1-k} where $k = 1, 2, \ldots, 10$. Excess returns are bootstrapped by resampling the weighted residuals using a high-dimensional factor model, to ensure sufficient simulation of the sample moments (up to 20 factors for $\omega \leq 0$, and 10 for $\omega > 0$). Pricing errors are then estimated for models with an increasing number of latent factors, all under the same data-generating process. Multiple-hypothesis testing biases are accounted for using the Benjamini and Hochberg (1995, BH) false discovery control approach. See Section IA.2.3 of the Internet Appendix for further details on the application of the wild bootstrap procedure.

[17]In unreported results, we find that this lower performance of PCA holds even when using larger models, i.e., including more than ten latent factors extracted by PCA.

[18]Importantly, high RP-weights can increase the risk of IS overfitting, with the superior performance likely reducing OOS given the large weight applied to the first moment.

IV.B Stability of the Factor Structure and Out-of-Sample Tests

IV.B.1 Latent Factor Stability Analysis

To investigate the stability of the optimal SDF over time, Figure 4 presents recursive estimates of the Sharpe ratios of the tangency portfolios consisting of factors $F_{1\text{–}k}$, for $k = 1, 2, \ldots, 10$. We use an initial window of 20 years, and proceed recursively to the end of the sample.[19]

[Figure 4 about here.]

One clear-cut finding is that the Sharpe ratio of the nine-factor model is quite stable over time, with a slight downward trend — the Sharpe ratio falls from 1.78 to 1.47 in around 20 years. This stability contrasts with the sharp decline in the performance of the AMP 50/50 combination, shown earlier. Looking at models of different dimensions, we can also see that the performance of the seven-factor model declines significantly from 2017 onward. Thus, F_8 and F_9 help compensate for the drop in performance of F_7, maintaining the stability of the Sharpe ratio. It can also be seen that the Sharpe ratio generated by the nine-factor model is indistinguishable from that of the ten-factor model. This reinforces the selection of the nine-latent-factor model as the optimal value–momentum SDF, based on the full-sample evaluation criteria.

IV.B.2 Out-of-Sample Performance

In Section IV.A, we selected the optimal pricing kernel using full sample information. Although we provide some evidence that the factor structure is quite stable over time using recursive estimation of the optimal SDF, there is still a legitimate concern that using full sample information one may select a richer factor model than required, hence inducing the risk of overfitting IS and underperforming OOS. Thus, we perform some OOS tests. Specifically, we provide evidence on the evaluation of the performance of latent-factor models OOS, for varying RP-weights (with $\omega = -1, 20, 50$) and dimensions (with $k = 1, 2, \ldots, 10$ factors). Factors and loadings are estimated recursively, to approximate the real-time behavior of a representative US investor, with

[19] Figure IA.5 shows recursive tests for the null of no alpha starting from 2003 (using the first twenty years of data for initial factor extraction). The results confirm clearly that: (i) at no point during the sample more than nine factors are required to deliver zero alpha; (ii) nine factors were required already early in this sample, corroborating the notion that more parsimonious models would leave unexplained returns; (iii) the most parsimonious model during the sample would have had at least seven factors; (iv) in the last ten years the inclusion of the eighth, and possibly ninth, factors is central to eliminating all alphas.

an initial window of 20 years. The OOS setup then closely follows LP and NSZ.[20]

[Table 2 about here.]

The results are reported in Table 2. First, note that the IS Sharpe ratio is 1.40 during the sample period 2003-2023. This is useful as a benchmark for the OOS results over the same period. Second, using $\omega = 20$, the OOS Sharpe ratio for the nine-factor model is 1.07 over the same period. Therefore, as one would expect, there is some deterioration when moving from IS to OOS analysis (Sharpe ratio from 1.40 to 1.07). Yet, the Sharpe ratio is an order of magnitude higher than the Sharpe ratio of 0.44 obtained with a 50/50 combination.[21] Third, the nine-factor model has not only a higher Sharpe ratio, but also lower average pricing errors, and lower idiosyncratic variance than more parsimonious models. This confirms the need for a rich latent factor model also OOS. Finally, consistent with the IS analysis, RP-PCA performs better than PCA although, as expected, the gains reduce OOS. At the same time, we find that there is no benefit from using weights that are higher than $\omega = 20$. In fact, $\omega = 50$ produces results that are very similar to $\omega = 20$, if not slightly worse.[22]

Alternative Test Assets. So far, we have assessed the OOS performance of the latent-factor model in the time series, by predicting one-period-ahead returns using recursive estimates of the risk exposures. Next, we assess the OOS performance in the cross section, by examining the ability of our latent-factor model to price the returns of assets that were not used to extract the latent factors. In this sense, the exercise is run OOS in the cross-section. However, it is important that these new test assets represent the returns of alternative value and momentum sorts. This is because we do not expect the latent-factor SDF to price investment strategies other than value and momentum, as we do not claim that our factor model can price all assets and investment strategies. A natural choice is therefore to use the following popular Fama-French portfolios: (i) 25 developed market size–value excess returns; (ii) 25 developed market size–momentum excess returns; and, (iii) 50 developed market size–value and size–momentum

[20] In short, factors and loadings are estimated recursively. Using the estimated loadings, including information up to time t, we predict the factors and the returns at $t + 1$, thereby obtaining pricing errors at $t + 1$. The maximal Sharpe ratio is estimated using weights formed only from the recursive period (i.e., up to time t). The mean and variance of the OOS pricing errors are used to construct estimates of the average root-mean-square pricing error and idiosyncratic variation, respectively.

[21] Note that the 50/50 combination is essentially constructed using only available information at the time of sorting and hence there is no difference between IS and OOS performance. A caveat here is that the AMP factors themselves are constructed using inverse volatility weights with full sample information. AMP discuss robustness to alternative weighting schemes, such as rolling-window estimation.

[22] Note also that in the OOS analysis, the model performance does not necessarily improve monotonically as one adds more factors to the SDF (see also LP and NSZ).

excess returns, respectively.[23]

[Figure 5 about here.]

Figure 5 presents the pricing evidence using these three cross-sections with the nine-factor model. The resulting evidence shows that the pricing performance of the nine-factor model is quite good (particularly given the presence of a systematic factor, size, which is not intended to be priced by the optimal value–momentum pricing kernel). The goodness of fit measures are high, ranging from 55.6% using the 25 size–value portfolios to 79.9% using the size–momentum portfolios. Using the joint set of 50 test assets, the cross-sectional R^2 is 63.1%. Regardless of the cross-section, the wild bootstrapped MAEs are statistically insignificant and no individual alpha is statistically significant, at the BH-corrected 5% level. We can therefore conclude that the optimal factor model is also able to price the Fama-French set of developed market equity value and momentum portfolio excess returns.

IV.C The latent-factor model and the AMP-factor model

In this section, we assess how the nine-latent-factor model compares to AMP's three-factor model using simple spanning regressions. The spanning regressions allow us to address whether the AMP factors subsume the tangency portfolio returns from the nine-factor SDF, and vice versa, without having to rely directly on specific choices of test assets (i.e., Barillas and Shanken 2017). We perform the regressions over the full sample period, from 1983, and over the sub-sample starting after 20 years, in 2003.

First, the results in Table 3 shed light on whether the information in the nine latent factors of the SDF is subsumed by the AMP factors, i.e. we run regressions of the individual nine latent factors, one by one, on the AMP factors. We find that the AMP factors capture only partly the information in the latent factors. In particular, the AMP factors fully explain the alphas of F_1 and F_9, but not those of F_4, F_7 and F_8 which have the highest Sharpe ratios (Panel A1). The unexplained alphas and Sharpe ratios are economically significant. For example, the Sharpe ratios unexplained are 0.13, 0.14 and 0.13 for F_4, F_7 and F_8, respectively (see column SR_α).[24] Interestingly, F_4 is the only factor with exposures of opposite sign to the AMP value

[23] While the optimal latent-factor model is constructed using a range of asset classes and markets, the Fama-French test assets include only equities. We choose these assets because they are widely used in the literature and are readily available. In addition, although they are restricted to one asset class, they are not restricted to only one geographical region and cover the equity markets of several developed economies.

[24] Of course, factors 2, 3, 5, and 6 are time-series factors and therefore have no alpha to be explained. However, we find that these factors are poorly explained by the AMP factors, with R^2s reaching at most 3%. In contrast, the risk-premium factors show much higher R^2s, except for F_7.

and momentum returns. Specifically, F_4 increases with momentum and decreases with value. Hence, this factor appears to capture (at least part of) the negative correlation between value and momentum strategies originally documented by AMP and confirmed in this paper.[25] In contrast, F_8 and F_9 co-move with both value and momentum, while F_7 seems to be related only to value. We find that these results also hold in the more recent sample (Panel A2), perhaps even more clearly.

[Table 3 about here.]

Second, in Panel B of Table 3, we replace the latent factors with the tangency portfolios' excess returns, including an increasing number of factors, i.e. we run spanning regressions of tangency portfolio excess returns from the latent factor model on the AMP factor model. The resulting evidence is clear cut. The AMP three-factor model is unable to fully span the latent-factor tangency portfolio if the latter consists of more than three factors, as the alphas are highly statistically significant. Using the full sample, only about 42.60% of the variation in the nine-factor SDF is explained by the AMP factors, with an unexplained Sharpe ratio of around 0.22. This Sharpe ratio is even larger in the post-20-year sub-sample, rising to 0.35. It is therefore clear that the factor structure of the optimal value–momentum SDF contains pricing dynamics beyond that captured by the benchmark AMP model.[26]

It is also evident that the latent-factor tangency portfolio is somewhat segmented with respect to the AMP factors, in the sense that there are essentially three parts of the latent factor SDF. The component that is subsumed by the AMP factors ($\pi(F_1) - \pi(F_{1-3})$) is mainly related to the market factor and somewhat to value. However, when F_4 enters the SDF, the information changes substantially. In fact, $\pi(F_{1-4}) - \pi(F_{1-6})$ show positive exposures to momentum (and the market) and negative exposures to value. These factors therefore seem to capture momentum and the diversification benefits from combining value and momentum (although this result is somewhat weaker in the sample after 20 years). Finally, the remaining SDFs, $\pi(F_{1-8}) - \pi(F_{1-9})$, are positively exposed to both the value and momentum AMP factors, as well as to the market

[25] Specifically, this point is discussed and elaborated further in Section IV.E, when we examine the results of the third pass. Nevertheless, it is reassuring that this behavior is captured by the optimal SDF, given the key role of the negative correlation between value and momentum in generating high Sharpe ratios both in the AMP strategy and in our own proposed latent-factor SDF.

[26] As mentioned earlier, another possible benchmark model is the non-tradable five-factor model of Cooper et al. (2022). The asset pricing results of this model are presented in Figure IA.2 in the Internet Appendix, alongside the nine-factor model, the AMP model and the CAPM, over the same time-series for comparability. This model is also unable to price fully the cross-section of test asset excess returns. Nevertheless, as the factors themselves have a macro-financial interpretation, they are included as candidate factors in the third pass, in Section IV.E.

factor.

[Table 4 about here.]

To conclude the spanning analysis, we then reverse the exercise, by regressing the AMP factors on the latent-factor tangency portfolios with an increasing number of factors. Table 4 shows that the nine-factor model explains fully the information in the AMP factors, with some alphas becoming insignificant even with more parsimonious models (e.g., momentum has no alpha left when regressed on $\pi(F_{1-4})$). In the sub-sample after 20 years, a two-factor model is sufficient to capture the information in the AMP model. See Table IA.6, in the Internet Appendix, for evidence using the individual SS and AA AMP factors.

Taken together, this analysis suggests that the information in the AMP factors is fully subsumed by the latent factors. However, the reverse is not true, in that the AMP factors only explain part of the information in the latent factors. In this sense, there are value and momentum leftovers, i.e., excess returns available in the cross-section of value and momentum portfolio excess returns that are not priced by the three-factor AMP model but that are priced by the nine latent-factor model. Moreover, this regularity seems to be intensified in the later sample. This also suggests that there are additional returns that an investor can earn by combining value and momentum test assets freely over combining value and momentum factors separately as in (high-minus-low or) rank strategies, which are inherently more restrictive. Indeed, by implementing RP-PCA on the joint cross-section of value and momentum portfolios, the approach we use is both agnostic and flexible in the way the factors entering the SDF are constructed. We will further shed light on this issue in the subsequent sections.

The evidence presented thus far demonstrates that the identified nine-latent-factor SDF prices well the cross-section of test assets, both IS and OOS. It does so better that the seminal benchmark model of AMP, particularly owing to the benefit of the advances in asset pricing and statistical methods that have been developed over the last decade. Now that the optimal pricing kernel has been established, the remainder of the analysis focuses on refining our understanding of the drivers of this factor structure.

IV.D Tangency Portfolio Decomposition

A powerful result of AMP, which is an important facet of asset-class-specific factor models, is the diversification benefits of combining value and momentum trading strategies. In fact, by combining their value and momentum factors, the 50/50 combo yields a Sharpe ratio of 1.10 in our updated sample, while the respective Sharpe ratios for value and momentum are merely 0.47 and 0.50. This is because the two factors are strongly negatively correlated.

However, so far we have shown that the nine-factor SDF appears to perform even better than the original three-factor SDF proposed by AMP, despite using the same value and momentum portfolios. In this section we try to identify more clearly what is driving the superior performance of the latent-factor SDF. We note that in AMP, as usual in most asset pricing studies, factors are constructed using specific signals in isolation. That is, AMP construct the value factor from the value portfolios and the momentum factor from the momentum portfolios. The two factors are then included separately in the three-factor SDF, or are used to form the 50/50 combo. This means that the value and momentum portfolios are combined in a restrictive way. This reasoning extends to the way that markets/asset classes are combined, for a given strategy. Therefore, some of the benefits of combining value and momentum are not exploited. In contrast, RP-PCA allows us to combine the value and momentum portfolios freely, both along the strategy (value/momentum) and the asset class/market dimensions, giving more weight to high risk premium portfolios in accordance with the objective function of RP-PCA.

In what follows, to better understand the drivers of the superior performance of the latent-factor SDF, we decompose the Sharpe ratio of the optimal tangency portfolio into two key components: (i) the Sharpe ratio attributable to the combination of value and momentum "factors" extracted from *separate* cross-sections of test assets, and (ii) a residual orthogonal component, which is not captured by forming factors from separate cross-sections — in the traditional asset pricing fashion — but rather by exploiting the full covariance matrix of the *joint* cross-section of excess returns.

To this end, we proceed as follows. First, we form two SDFs, one for value and one for momentum. To do this, we follow the same steps as before, but we apply RP-PCA with $\omega = 20$ to the two cross-sections separately, i.e., to the 24 value and the 24 momentum portfolios.[27] We determine the optimal number of latent factors entering each SDF using the same evaluation criteria as before: it turns out that for both cross-sections nine latent factors are needed to span the respective cross-sections (for brevity, we report the diagnostics in Table IA.7 in the Internet Appendix). Using mean–variance weights, we then form the two separate value, π_V,

[27] In one of their exercises, LP apply RP-PCA to the 25 Fama-French double-sorted portfolios, which is very close to the cross-sectional dimension of the two separate cross-sections we study. This should help alleviate concerns about the small N used in this application.

and momentum, π_M, tangency portfolios.

Table 5 shows the excess returns and Sharpe ratios of the π_V and π_M tangency portfolios (first two panels). In this table we scale the excess returns of each tangency portfolio such that the one-factor model has 10% annualized volatility to ease comparability. While we report excess returns for SDFs with an increasing number of factors, F_{1-k}, for $k = 1, 2, \ldots, 9$, for our purpose we focus on the two nine-factor models. The two tangency portfolios give very similar Sharpe ratios, 0.99 and 0.98 for π_V and π_M, respectively. In the third panel, we then combine the two value and momentum tangency portfolios, again using mean–variance weights. The resulting tangency portfolio, $\pi_{V/M}$, has a Sharpe ratio of 1.18. This confirms that there are also diversification benefits from using a different approach to AMP in constructing the two separate value and momentum factors/tangency portfolios.[28] These benefits are somewhat less evident in our case, as the individual value and momentum tangency portfolios start with much higher Sharpe ratios than the AMP factors, since they both include exposure to a level market factor. However, regardless of the approach used to construct the value and momentum "factors", the resulting Sharpe ratios are smaller than those obtained by applying RP-PCA to the joint cross-section of 48 test assets (recall that π_{VM} has a Sharpe ratio of 1.47), which indicates that part of the enhanced performance of our optimal latent-factor SDF and tangency portfolio stems from being able to combine freely the value and momentum portfolios.

[Table 5 about here.]

To quantify the relative importance of these different components of the overall tangency portfolio excess returns, we again recur to spanning regressions. Specifically, we regress the excess returns of the joint value and momentum tangency portfolio π_{VM} on the excess returns of the tangency portfolios of the two separate value and momentum tangency portfolios ($\pi_{V/M}$). We scale all variables by their respective standard deviations, so that the output of the spanning regression is directly interpretable as a decomposition of the maximal Sharpe ratio of π_{VM}. This allows us to recover the Sharpe ratio contributions of the component arising from the combination of separate value and momentum factors (R_S, spanned), and the residual component

[28] Figure IA.6 in the Internet Appendix presents the output from estimating a dynamic conditional correlation (DCC) model applied to the optimal tangency portfolios of each of these strategies (Engle, 2002). This is estimated on the orthogonalized components of each strategy, extracted by projecting the value (momentum) tangency portfolio on the momentum (value) portfolio and by taking the residuals. This is equivalent to stripping out the common factor structure shared by value and momentum. On average, the DCC is −0.31, which is consistent with the previous literature regarding the negative correlation of value and momentum factors (spread or rank portfolios). The graph also shows that the correlation is persistently negative over the sample, with clear time variation but fairly tight bounds.

arising from fully exploiting the covariance matrix of the joint cross-section of test assets, i.e. from freely combining value and momentum portfolios (R_U, unspanned). This method of decomposition is similar to that employed by Campbell et al. (2025) to separate the value factor into the intra-industry and inter-industry components. Indeed, we could alternatively refer to our spanned and unspanned components as the *intra* and *inter* components of value and momentum, respectively.

From this decomposition, we find that the Sharpe ratio attributable to the spanned component is 0.96, which explains about 65% of the Sharpe ratio of the optimal tangency portfolio, π_{VM}. As a result, the unspanned component accounts for the remaining 0.51 of the total Sharpe ratio. Figure 6 illustrates this decomposition in terms of cumulative returns over the sample period. The spanned component, R_S, accounts for two-thirds of the returns of the optimal tangency portfolio (R_{VM}). However, the one-third owing to the unexplained component, R_U, is the source of economic gain that suboptimal asset allocation strategies fail to capture, by constructing pricing factors in isolation.[29]

[Figure 6 about here.]

The relative performance of the optimal pricing kernel is illustrated by Figure 7, which plots the efficient frontiers for each of: the full optimal nine-factor model (*Val&Mom*); the mean–variance combination of the separate nine-factor value and momentum models (*Val/Mom*); and, each of the separate value (*Val*) and momentum (*Mom*) models, respectively. Combining the two separate value and momentum tangency portfolios enhances the attainable frontier, due to the diversification benefits of investing in both strategies (AMP), and the natural expansion of the universe of test asset returns. Manifestly, however, the efficient frontier of the optimal nine-factor pricing kernel dominates all other strategies. In sum, incorporating all the information from the variance-covariance matrix of the full universe of test asset returns leads to superior asset allocation performance.

[Figure 7 about here.]

We corroborate the latter point by conducting Monte Carlo simulations to assess whether the superior performance of the tangency portfolio π_{VM} over $\pi_{V/M}$ also occurs in a simulated

[29] In the Internet Appendix, in Figure IA.4 we show the weights of the tangency portfolio on the 48 value and momentum test assets, as well as the test asset individual contributions to the overall tangency portfolio risk premium. First, it is clear that no specific asset class dominates the portfolio return. Second, while there is monotonicity in some specific asset-class/market terciles (e.g., US equities value) this is not universally true (e.g., US equities momentum). This flexibility is not permitted when using fixed weighting schemes, such as high-minus-low or rank.

environment. We set up the simulation exercise in a manner similar to that of GX and NSZ. Specifically, the data-generating process (DGP) is driven by the latent factors. Importantly, we find that using this DGP the simulated test asset returns have statistical properties (means, standard deviations, and Sharpe ratios) that closely match those of the observed test asset returns. This, in turn, makes the simulation analysis reliable. In what follows, we briefly summarize the main findings from the simulations, and provide full details in the Internet Appendix (Section IA.5.5).

We find that the simulation exercise confirms the outperformance of π_{VM} over $\pi_{V/M}$, as the vast majority of simulations (9971 out of 10000, or 99.71%) produce a Sharpe ratio of π_{VM} greater than that of $\pi_{V/M}$. Moreover, the unspanned component, R_U, accounts for roughly 31% of the Sharpe ratio of π_{VM} on average (broadly consistent with the in-sample evidence), with the 5^{th} and 95^{th} percentiles being about 20% and 40%, respectively. These simulations therefore reassure us that the superior performance of π_{VM} over $\pi_{V/M}$ is not sample specific. This lends support to the empirical finding that combining value and momentum test assets flexibly to construct the factors that enter the tangency portfolio leads to a better risk-return trade-off than combining the two separate value and momentum tangency portfolios. In short, valuable information is lost when combining solely the *intra* value and momentum factors, rather than the *inter* value and momentum factors.

Taken together, these results highlight two important points. First, in general, it is suboptimal to construct factors from individual strategies or asset classes and subsequently combine them into a model to price the joint cross-section, as this leads to a loss of information, e.g., by not capturing all pairwise test assets' covariances which can indeed be both statistically and economically significant. Second, and more specific to our study, the improvement of the efficient frontier by freely combining value and momentum portfolios across both strategies and asset classes/markets is economically large relative to simple combinations of value and momentum factors. This suggests that there are additional risk-adjusted returns beyond those that can be obtained from the negative correlation between value and momentum factors, call them leftovers.

IV.E Third-Pass Evidence: Candidate Factor Exposures and Risk Premia

Next, we turn to the third pass. This analysis provides robust estimates of the risk exposures (Table 6) and risk premia (Table 7) of a long list of macro-financial tradable and non-tradable candidate factors. In addition, we also treat as candidate factors the tangency portfolio excess returns and its components, primarily to better relate these components to the latent factors and shed light on which parts of the SDF (and which macro-financial risks) drive the spanned and unspanned components of excess returns. We focus first on the return components of the optimal tangency portfolio (Panel A) and then on the tradable and non-tradable macro-financial candidate factors (Panels B-C).

Specifically, Table 6 presents estimates of the loadings from Equation (9), the time-series spanning regressions of the candidate factor innovations on each of the de-meaned latent factors, η_{F_k}, as well as the explained variation, R^2_{1-k}, for factors F_k where $k = 1, 2, \ldots, 9$, corresponding to the optimal nine-factor model. Then, using factor models including up to nine factors, Table 7 shows the candidate factor risk premia from Equation (10a), given by the latent factor prices of risk multiplied by the candidate factor exposures to the latent factors, and the Sharpe ratios of the cleaned candidate factors from Equation (10b). In both tables, we only report the candidate macro-financial factors with significant three-pass risk premium estimates at the five percent significance level using the optimal nine-factor model. From a list of 94 candidate factors, this amounts to 34 factors, plus the 5 tangency portfolio-related factors.[30]

IV.E.1 Tangency portfolio components

To begin with, we examine the behavior of R_{VM}. By construction, the nine latent factors explain 100% of its variation (Table 6, Panel A), with the exposures corresponding exactly to the mean–variance weights presented in Table 1 (Panel A1, $\widehat{b}_{MV,k}$). Also, as expected, the factors with the largest exposures are the most critical pricing factors in Table 1. More notable, however, is that F_8 explains about 40% of the time-series variation of R_{VM}, with the first six factors accounting for only 30%.

[Table 6 about here.]

It is then instructive to look at the behavior of R_S and R_U, which are remarkably different. Factor R_S – the component that combines value and momentum tangency portfolios (separately constructed) using mean–variance weights – loads positively on factors F_1 to F_8, and negatively on F_9. Thus, similar to R_{VM} (except for factor nine), all latent factors are also procyclical sources of risk for R_S. However, the importance of each factor differs. The first seven factors

[30] For the full range of candidate factor exposures and risk premia, see Table IA.8 and Table IA.9, respectively, in the Internet Appendix.

account for about 80% of the time-series variation in R_S, with F_1 having an R^2 of around 40%. Thus, factors eight and nine play a much less relevant role in explaining R_S than R_{VM}.

In contrast, factors F_8 and F_9 are particularly relevant for R_U: not only do they have the highest exposures, but they also account for most of its time series variation. Specifically, the R^2 jumps from 15% to 88% by adding factors eight and nine, with the two factors showing similar contributions. This confirms that the benefits of freely combining value and momentum portfolios are mainly captured by these two factors. Furthermore, we find that the only other economically relevant source of procyclical risk for R_U is factor four (factors six and seven also have statistically significant loadings, but lead to small increases in the R^2). In contrast, R_U loads negatively on factors one and two, which explains why R_{VM} is less exposed to these factors than its spanned component R_S. Put differently, the unspanned component is a hedge factor against these sources of risk, captured by factors one and two.

Panel A also includes the returns to the individual value, R_V, and momentum, R_M, tangency portfolios. This allows us to link the latent factors to the value and momentum factors. From the joint behavior of the ηs and R^2s, it is clear that factor four is a momentum factor to which value is negatively exposed, while factor seven is a value factor that is much less relevant to momentum. At the same time, factor one is an important source of procyclical risk for both R_V and R_M. Factors eight and nine show little relevance for both individual strategies, confirming that their relevance only emerges when value and momentum portfolios are freely combined.

[Table 7 about here.]

To complete this analysis, we turn to the risk premium estimates. Table 7, Panel A, shows that the risk premium of R_{VM} is significant at the one percent level regardless of the number of latent factors. Moreover, as a sanity check, we note that using the nine-factor model, the Sharpe ratio of R_{VM} is exactly the same of that presented in Table 1. As for the components, four-fifths of the Sharpe ratio of R_S is explained by factors one to seven. In contrast, the Sharpe ratio of R_U is almost entirely explained by factors eight and nine. However, factor eight is by far the most important pricing factor, even though the two factors have similar exposure estimates and explained variation in Table 6.[31] It is also evident that the sign of the risk premium of

[31] Cleaned from measurement-error and omitted-variable biases, R_S and R_U have higher Sharpe ratios than their raw counterparts presented in Table 5. In addition, the cleaning makes the factors slightly positively correlated, despite the fact that the two (raw) factors were originally orthogonal by construction. This means that in order to accurately recover the Sharpe ratio of R_{VM} by combining the two cleaned factors, their correlation must be taken into account.

R_U changes with the dimensionality of the SDF. It becomes positive and highly statistically significant only with the eight-factor model. To visualize the contribution of the latent factors to the estimation of candidate factor risk premia, Figure 8 shows the evolution of the cumulative returns of R_{VM}, R_S, and R_U cleaned using latent factor models of increasing dimension.

[Figure 8 about here.]

Finally, we evaluate the risk premium estimates and Sharpe ratios of the value and momentum factors, R_V and R_M, respectively. We find that a large SDF is indeed needed to fully recover their risk premia. However, the two factors behave differently when latent factors are successively added to the SDF. Using a three-factor model, we can only recover a small fraction of their premia and Sharpe ratios. Adding factor four almost doubles the risk premium of momentum, while reducing that of value by one third. This shows that the negative correlation between value and momentum, captured by factor four, has important pricing implications. Indeed, factor four affects both the Sharpe ratio and the risk premium estimates of value and momentum, being a countercyclical source of risk for value and a procyclical source of risk for momentum. Factors seven and eight are then required for an accurate recovery of the value risk premium, while they are relatively less important for momentum. Using the nine-factor model, the Sharpe ratios of the cleaned value and momentum factors are 1.05 and 1.07, respectively.

IV.E.2 Macro-financial factors

Next, we assess the macro-financial risks priced into the joint cross-section of value and momentum portfolios. Table 6, Panel B, shows that among the tradable factors considered, a few hedge fund strategies have significant exposures. All factors have negative loadings on the level factor (factor one), except for FX carry, which has a positive exposure and is the only tradable factor in this set expected to be procyclical. For most of these candidate factors, the remaining latent factors are much less relevant, leading to limited increases in the R^2s. However, the hedge fund commodity (*comstrad*) and bond (*bdstrad*) straddle factors stand out, as the former has a highly significant positive exposure to factor four and the latter has a positive exposure to factor nine. The hedge-fund factors have negative risk premia and hence are countercyclical factors. This is consistent with these factors capturing returns from selling straddle strategies, hence being short volatility, by which hedge funds provide volatility insurance to market participants (Agarwal and Naik, 2004). In line with previous literature, the carry factor has a positive risk premium, being a procyclical factor (Lustig and Verdelhan, 2007; Menkhoff, Sarno, Schmeling and Schrimpf, 2012a; Nucera et al., 2024).

Moving to the non-tradable macro-financial factors (Panel C), we find that many factors have relatively high R^2s. Thus, the latent factors seem to capture a variety of risks that span several macro-financial categories. In particular, they relate to financial uncertainty (*gfc*, *vix*/*vxo*, *impar*), liquidity (*icap*), crash risk (*adbear*), and behavioral (*dtoat*, and *dtoy*) factors, with R^2s above 45%, which are high for non-tradable factors. For most of these factors, the high R^2s are due to their exposure to the level factor. For example, the level factor is positively related to the global financial cycle factor (*gfc*) of Miranda-Agrippino and Rey (2020), the intermediary capital risk factor (*icap*) of He, Kelly and Manela (2017) and the behavioral factors (*dtoat* and *dtoy*) of Li and Yu (2012), while it decreases with stock market implied volatility (*vix*/*vxo*) and the crash risk factor (*adbear*) of Lu and Murray (2019).[32]

However, some of these high R^2 factors also appear to be highly exposed to the remaining latent pricing factors: for example, we see economically large increases in the R^2s of the intermediary and behavioral factors when moving to a nine-factor model. We also find a close association of several priced interest rate and monetary policy factors with parts of the SDF beyond factor one, including its leftover component. In particular, the US long-term yield change (*ltychg*), term spread (*trm*) and the Cooper et al. (2022) term spread factor (*uts*) have negligible exposures to the first three latent factors, and yet their R^2s increase substantially by adding the remaining latent factors.

The exposures to factor four are of particular interest, since this factor is related to the diversification benefits from investing in both value and momentum strategies. We find that factor four gains when global financial conditions worsen, the TED spread widens, and intermediaries' risk-bearing capacity declines. This is consistent with the notion that value strategies perform poorly in periods of financial market stress, while momentum strategies perform relatively well. At the same time, long-term interest rates are negatively exposed to factor four. This is consistent with the idea that the relationship between momentum and value strategies varies with the level of interest rates, in the sense that momentum returns decline while value

[32] Factors *dtoat* and *dtoy* are two related measures of underreaction and overreaction to news, constructed from scaled differences to Dow Jones index highs. There is a vast and evolving literature that attempts to rationalize momentum returns as a result of investors failing to immediately incorporate information into asset prices. See Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999) for theories of initial under- and delayed overreaction. See also Goyal, Jegadeesh and Subrahmanyam (2025), for a recent example of empirical evidence on such mechanisms.

returns increase as interest rates go up. This is because momentum co-moves positively with factor four, while value co-moves negatively. However, interest rates are also negatively exposed to factor seven, which is mainly a value factor, as previously shown. Taken together, these findings seem to suggest that interest rates can (only) partly explain the negative correlation between value and momentum, as other sources of risk are also relevant.[33]

Turning to the risk premium analysis, Table 7 shows that several macro-financial factors, when corrected for measurement error and converted into return-based factors, deliver high (absolute) returns and Sharpe ratios. In fact, many of these factors have Sharpe ratios close to one. For example, the Sharpe ratios of interest rate and monetary policy factors range from 0.68 to 1.08. Among these factors, the US term spread (*trms*) and long-term bond yield change (*ltychg*) factors have the highest Sharpe ratios. Specifically, *trms* and *ltychg* have negative risk premia, meaning that they are countercyclical factors. This is, for example, consistent with the notion that the term spread, or simply the slope of the yield curve, is a powerful barometer of financial and economic conditions and is associated with recessions. Moreover, we find that the Sharpe ratios of several measures of US monetary policy surprises, such as those of Bauer and Swanson (2023) and Jarociński (2024) (*mpbs* and *mjsummp*), are also particularly high. This suggests that US monetary policy is a risk factor for several investment strategies everywhere for which investors demand compensation. Their risk premia are also negative, so that the tangency portfolio returns decline (increase) with US tightening (easing) monetary policy shocks, i.e., with positive (negative) yield surprises. Moreover, in contrast to other macro-financial risk factors, a large part of the premia of the interest rate and monetary policy factors seems to come from the leftovers — here, meaning latent factors four, seven and eight, as they cannot be fully explained by the AMP factors. Similar considerations apply to the macro factor (*dei*) of Cooper et al. (2022), which measures changes in expected inflation.[34] We shed further light on the relation of the tangency portfolio components and the macro-financial risk factors in the next section.

We also find that many financial uncertainty factors yield quite high Sharpe ratios. Among them, the Merrill Lynch option volatility index (*move*) and the TED spread (*ted*) have Sharpe

[33] A number of studies have examined the role of interest rates, or discount rates, in driving equity value returns (Maloney and Moskowitz 2021; Campbell et al. 2025; Gormsen and Lazarus 2025, among others) and specifically their correlation with momentum. We are instead mainly interested in determining whether interest rates are a priced source of macro-financial risk in the combined value and momentum cross-section (everywhere not just in the US equity market), and whether they relate to both the spanned and unspanned components, and hence to which latent factors.

[34] Overall we find that a subset of the factors considered by Cooper et al. (2022) is priced (i.e., *dei*, and *uts*), when accounting for measurement-error and omitted-variable biases.

ratios of 0.92, also thanks to the relevant contribution of factors four and eight. The skewness factor (*skew*) of Jondeau, Zhang and Zhu (2019), which measures the cross-sectional skewness across firms, also has a Sharpe ratio around 0.92, with significant contributions from factors four and eight. Notably, the risk premium of the text-based financial crisis indicator (*emvfincri*) of Baker, Bloom and Davis (2016) only becomes significant when including factors eight and nine.

Summing up, we find that several sources of macro-financial risk are priced in the cross-section of value and momentum portfolios. Importantly, we show that in order to obtain accurate estimates of these premia, it is necessary for the SDF to fully span the cross-section of test assets. Indeed, the premia of some of the candidate factors change significantly when moving to larger latent factor models. This highlights again the importance of accounting for leftovers, as their omission can lead to an inaccurate characterization of the risk-return trade-off inherent in the cross-section of returns of value and momentum investment strategies, as well as of the macro-financial sources of the trade-off. As a note of caution, the three-pass procedure allows us to identify the priced macro-financial risks, but these are not necessarily the true, fundamental risk factors. Thus, we next attempt to shed light on the identities of the macro-financial factors that are related to the returns of the tangency portfolio. In addition, we will also explore further the relationship between the components of the tangency portfolio returns and the priced sources of macro-financial risk.

IV.F Shrinking the Candidate Factor Universe

To begin with, Table 8 presents univariate spanning regressions of R_{VM}, R_S, and R_U on the cleaned factors which display statistically significant risk premia using the optimal nine-factor model (hence the same 34 factors as in Table 6 and Table 7, Panels B-C). Thus, all candidate factors are return-based and free from measurement error. (We present the evidence for all macro-financial factors in the Internet Appendix, Table IA.10.)

[Table 8 about here.]

A first clear finding is that the explained variation is orders of magnitude larger for R_{VM} and its spanned component, R_S than for the unspanned component, R_U. This is understandable, as many of these macro-financial risk factors have significant risk premia due to their high exposure to the level factor, which is far less important for the unspanned component. However, several macro-financial factors, many of which have already been identified in the earlier analysis, help explain a non-negligible portion of the time-series variation in the unspanned factor. These factors include *dei*, *trms*, *icap*, *ltychg*, *dtoat*, *dtoy*, *gfc*, and *vix/vxo*.

Second, while R_S is exposed to all 34 macro-financial risk factors, R_U is exposed only to a subset of factors. Moreover, R_S and R_U are exposed to some of these factors with opposite signs. For example, R_S and R_U have positive and negative exposures to *icap*, respectively. This implies that R_{VM} has some macro-financial risk exposures that are smaller, in absolute terms, than R_S. However, this is not the case for all factors: for example, *dei*, *trms*, and *ltychg* co-move with both (spanned and unspanned) components in the same direction. This suggests that R_U can hedge some of the macro-financial risks to which R_S is exposed, but at the same time it is exposed to some of the same risks as R_S, particularly those arising from interest rates and monetary policy.

Third, all univariate regressions yield large, statistically significant intercepts, implying that neither the tangency portfolio nor any of its components can be fully captured by any single source of macro-financial risk. It is therefore natural to ask what combination of priced candidate factors can fully explain the tangency portfolio. A simple approach to reducing the dimensionality of the universe of candidate factors is to run spanning regressions of the optimal nine-factor tangency portfolio on the cleaned 34 macro-financial candidate risk factors. While the search for the best method to shrink the factor zoo is still ongoing, some recent asset pricing literature has relied on penalized regressions. For example, Kozak, Nagel and Santosh (2020) apply both L^1 and L^2 norm penalizations, similar to an elastic net approach, to reduce the dimensionality of the SDF. Here, we employ LASSO (rather than ridge or elastic net) to enforce maximum shrinkage of the cross-section of candidate factors (allowing loadings to shrink to zero). Importantly, this reduced-form model is *not* being proposed as the optimal model for pricing value and momentum. Rather, it is a simple exercise to better understand the key risk drivers of the optimal SDF identified in this sample.

Figure 9 shows the nine macro-financial factors selected by LASSO: *emvfincri*, *trms*, *eqstrad*, *ltychg*, *comstrad*, *jkpdebiss*, *gfc*, *dtoy*, *emvinf*. The left panel (Loadings) shows the loadings of the selected factors. We note that most factors retain the same signs of the loadings as in the univariate regressions, despite some of these factors being correlated. In the middle panel (Loadings × Risk Premia), we multiply the estimated factor loadings with the factor risk premia. This allows us to better determine the economic relevance (contribution) of each factor (regressor) in explaining the tangency portfolio returns. Clearly, the term spread and changes in US long-term bond yields, captured by *trms* and *ltychg*, play a crucial role in understanding the drivers of value and momentum risk, as well as the financial crisis indicator of Baker et al. (2016). They are followed by the equity straddle hedge fund factor of Fung and Hsieh (2001), and by the under/overreaction indicator of Li and Yu (2012). The right-hand panel shows that, as expected, by including all nine selected de-noised factors in a simple OLS regression, we fully span the tangency portfolio returns, with zero average pricing errors.[35]

[Figure 9 about here.]

V Conclusions

A vast body of research has documented that value and momentum return premia are substantial both across different equity markets and in other asset classes. Starting from the influential work of Asness et al. (2013), this research has also shown that there is a strong common factor structure among value and momentum returns, and that they are negatively correlated with each other both within and across asset classes. Constructing separate value and momentum factors from a broad cross-section of returns everywhere and combining them with equal weights has generated high Sharpe ratios for a long time.

Yet, the experience of the last decade or so is that the performance of these strategies has deteriorated sharply. At the same time, even before becoming aware of such deterioration in performance, no empirical asset pricing model has been proposed in the literature that can fully price the cross-section of value and momentum portfolio returns everywhere, and hence some factors must be omitted in the models proposed thus far.

This paper restores the strong performance of a combined value and momentum investment strategy and the main insights of Asness et al. (2013), while also providing new insights both on the structure of the pricing kernel and on the macro-financial drivers. We are able to achieve this thanks to recent advances that allow us to efficiently recover the pricing kernel and conduct asset pricing analysis that is robust to both omitted-variable and measurement-error biases (Lettau and Pelger, 2020a,b; Giglio and Xiu, 2021).

[35]To conclude the analysis, Figure IA.10, in the Internet Appendix, presents the pairwise correlations of R_S and R_U with each of the cleaned candidate factor returns, highlighting those selected by LASSO in red. Among these selected factors, *trms* and *ltychg* have the highest positive correlations with both R_S and R_U. In contrast, *gfc* and *dtoy* co-move positively with R_S and negatively with R_U.

Our empirical evidence suggests that the optimal pricing kernel requires nine latent factors to price the joint cross-section of value and momentum and to maximize the Sharpe ratio of the tangency portfolio that invests in these portfolios. The Sharpe ratio of the tangency portfolio implied by this model in sample is 1.47 over the full 1983-2023, and 1.07 in the challenging out-of-sample period from 2003 to 2023. The recovery of the pricing kernel that prices fully the cross-section of value and momentum return premia is crucial to deliver this performance. Indeed, part of the performance of our optimal latent-factor SDF and tangency portfolio stems from being able to combine freely the value and momentum portfolios. Put simply, it is suboptimal to construct factors from individual strategies or asset classes and then combine them into a model to price the joint cross-section, as this leads to a loss of information.

The full specification of the nine-factor pricing kernel is also crucial to obtain estimates of the risk premia of candidate risk factors that can potentially drive the excess returns from investing in value and momentum combinations. We report risk premia estimates for some 100 factors and find that for many of them using more parsimonious latent-factor models provides inconsistent estimates due to omitted-variable bias. Thus, omitting the leftovers leads to an inaccurate characterization of the risk-return trade-off inherent in the cross-section of returns of value and momentum investment strategies, as well as of the macro-financial sources of the trade-off. A number of macro-financial factors have statistically significant risk premia, including factors related to interest rates, volatility, hedge fund trend-following factors, sentiment, and the global financial cycle.

Yet, we merely view our model as the first characterization of the risk-return trade-off in the global market of value and momentum strategies that can fully price value and momentum return premia. This pricing kernel is superior to previous models in a number of respects, but it is only one of potentially several alternative specifications. Future work could focus, for example, on conditional models of the joint factor structure of value and momentum, and on richer characterizations of out-of-sample forecasting that also takes into account transaction costs. We leave these developments to future research.

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Table 1
Latent Factor Pricing Diagnostics

The table presents model diagnostics of the first two steps of the three-pass asset pricing procedure of Giglio and Xiu (2021). Specifically, we examine the properties of the latent factors and associated tangency portfolios (Panel A), and the performance of the latent-factor models (Panel B). We do so by examining the first ten latent factors, i.e., F_k for $k = 1, 2, \ldots, 10$, and models including an increasing number of latent factors. We estimate the latent factors applying the RP-PCA method of Lettau and Pelger (2020a,b) with RP-weight of $\omega = 20$ to the 48 value and momentum test asset returns; in the Internet Appendix (Table IA.4), we present the same analysis for factors estimated using alternative penalty values. Specifically, Panel A1 shows the annualized average return of each latent factor (μ_{F_k}), where ***, ** and * indicate statistical significance at the 1%, 5% and 10% confidence levels, respectively, based on Newey and West (1987) standard errors; the k-th factor's Sharpe ratio (SR); and, the k-th factor's weight in the tangency portfolio ($\widehat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$). Panel A2 presents the annualized maximum Sharpe ratio of the tangency portfolios (SR), and the change in the Sharpe ratio owing to the inclusion of the next additional latent factor, k (ΔSR). Panel B provides several statistics and evaluation criteria for the first-pass (Equation (7): $\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}$) and second-pass (Equation (8): $\overline{X}_n = \widehat{\psi}_n \gamma^\top + a_n$) regressions, where X are the test asset returns, ψ are the asset risk exposures, and γ are the latent factor prices of risk (which, by no arbitrage equal the factor average returns). Panel B1 reports the average idiosyncratic variance ($\overline{\sigma}^2_\epsilon = 1/N \sum_{n=1}^{N} [Var(\widehat{\epsilon}_n)/Var(X_n)]$), and the average root-mean-square alpha (pricing error) from the time-series regressions ($\overline{\text{RMS}}_\alpha = \sqrt{\widehat{\alpha}\widehat{\alpha}'/N}$). Panel B2 shows the mean absolute pricing error from the cross-sectional regression (MAE), and the percentage of variation explained by the tangency portfolio (R^2). Panel B3 presents the number of individually statistically significant alphas for each factor model. The statistical significance of individual alphas and mean absolute pricing errors are estimated using a wild bootstrap procedure similar to that of Giglio et al. (2021), where multiple-hypothesis testing biases are addressed via the Benjamini and Hochberg (1995, BH) false discovery control approach. Thus, $\alpha^{BH}_{\xi\%}$ represents the number of individually significant pricing errors at the BH-corrected $\xi = \{10\%, 5\%, 1\%\}$ levels, respectively. See Section IA.2.3, in the Internet Appendix, for details of the wild bootstrap algorithm. The sample spans the 07/1983–12/2023 period, return data are at monthly frequency.

	Panel A: Factors & Tangency Portfolios						Panel B: Two-Pass Statistics							
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
$\omega = 20$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	42.56***	0.52	0.05	$\pi(F_{1-1})$	0.52	0.52	F_{1-1}	44.97	2.49	1.39***	74.42	31	28	19
F_2	9.37	0.26	0.06	$\pi(F_{1-2})$	0.58	0.06	F_{1-2}	33.92	2.26	1.10***	82.21	21	17	13
F_3	3.22	0.11	0.03	$\pi(F_{1-3})$	0.59	0.01	F_{1-3}	26.36	2.24	1.05***	83.67	17	16	13
F_4	11.37***	0.57	0.24	$\pi(F_{1-4})$	0.82	0.23	F_{1-4}	22.71	2.05	0.76***	92.16	19	16	10
F_5	2.93	0.13	0.05	$\pi(F_{1-5})$	0.83	0.01	F_{1-5}	18.63	2.03	0.71***	92.51	21	17	8
F_6	2.17	0.12	0.05	$\pi(F_{1-6})$	0.84	0.01	F_{1-6}	15.75	2.03	0.70***	92.65	19	16	12
F_7	9.57***	0.64	0.36	$\pi(F_{1-7})$	1.06	0.22	F_{1-7}	13.71	1.97	0.53***	96.10	22	15	5
F_8	12.66***	0.94	0.59	$\pi(F_{1-8})$	1.42	0.36	F_{1-8}	12.17	1.12	0.20	99.49	0	0	0
F_9	5.76**	0.39	0.22	$\pi(F_{1-9})$	1.47	0.05	F_{1-9}	10.40	0.79	0.13	99.78	0	0	0
F_{10}	0.41	0.03	0.02	$\pi(F_{1-10})$	1.47	0.00	F_{1-10}	9.16	0.79	0.13	99.80	0	0	0

Table 2
Out-of-Sample Fit of Latent Factor Models

The table presents the out-of-sample (OOS) analysis. We report the maximum Sharpe ratio (SR) of the tangency portfolios, and the root-mean-square pricing error ($\overline{\text{RMS}}_\alpha$) and unexplained idiosyncratic variation ($\overline{\sigma}^2_\epsilon$) of the latent-factor models including an increasing number of factors. We conduct the analysis using several RP-weights ($\omega = \{-1, 20, 50\}$). We perform the OOS analysis as in Lettau and Pelger (2020b); thus, we use time-t loadings estimated recursively via RP-PCA to predict factors ($F_{t|t+1}$) and test asset returns ($X_{t|t+1}$) at time $t+1$. The optimal tangency portfolio weights are also estimated recursively using only information available at time t. Specifically, we use an initial expanding window of 20 years, so that the OOS analysis covers the 07/2003–12/2023 period. For comparison, we also report the Sharpe ratio of the optimal nine-factor tangency portfolio computed with RP-weight $\omega = 20$ over the same period ($\pi(F^{IS}_{1-9})$), where the test assets are the 48 value and momentum portfolios, sampled monthly from 07/1983–12/2023.

	$\pi(F^{IS}_{1-9}) = 1.40$									
$\omega = -1$	$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
SR	0.50	0.50	0.43	0.40	0.49	0.51	0.51	0.51	0.53	0.96
$\overline{\text{RMS}}_\alpha$	2.51	2.21	2.42	2.29	2.10	1.93	1.79	1.74	1.60	1.26
$\overline{\sigma}^2_\epsilon$	36.69	31.01	22.15	18.64	16.04	13.99	11.94	10.20	9.21	8.34
$\omega = 20$	$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
SR	0.51	0.52	0.47	0.55	0.66	0.70	0.99	0.96	1.07	1.06
$\overline{\text{RMS}}_\alpha$	2.43	2.18	2.36	2.12	1.92	1.78	1.55	1.44	1.31	1.15
$\overline{\sigma}^2_\epsilon$	36.27	30.79	21.58	18.11	15.60	13.95	12.81	11.03	9.47	8.45
$\omega = 50$	$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
SR	0.52	0.53	0.54	0.69	0.77	0.88	1.01	0.99	1.06	1.06
$\overline{\text{RMS}}_\alpha$	2.37	2.16	2.25	1.96	1.81	1.60	1.56	1.42	1.32	1.15
$\overline{\sigma}^2_\epsilon$	36.03	30.64	21.49	18.20	15.57	14.28	13.09	11.11	9.46	8.45

Table 3
Spanning Regressions of Latent Factors on AMP Factors

The table presents OLS spanning regressions of latent factors (Panel A) and tangency portfolios (Panel B) on the three tradable factors of Asness et al. (2013), and a constant (α), in the sense of Barillas and Shanken (2017). The factors and tangency portfolios are those estimated in Table 1. In Panel A, we regress the individual latent factors, F_k for $k = 1, \ldots, 10$, on the three AMP factors: the market (MKT), value (VAL_{EV}) and momentum (MOM_{EV}), plus a constant. We report the individual loadings of each tradable factor, as well as the R^2 (in percent). Specifically, the α shows the unexplained average return, while SR_α is the unexplained Sharpe ratio. The latter has the benefit of being scale invariant. In Panel B, we repeat the spanning analysis by replacing the latent factors with the tangency portfolios of increasing dimensionality, $\pi(F_{1-k})$ for $k = 1, \ldots, 10$. The left-hand panel uses the full sample (07/1983–12/2023), whereas the right-hand panel uses only observations after the first 20 years (07/2003–12/2023). ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

Panel A: Latent Factor Returns

	Full Sample						Post 20 Years					
	SR$_\alpha$	α	MKT	VAL$_{EV}$	MOM$_{EV}$	R^2	SR$_\alpha$	α	MKT	VAL$_{EV}$	MOM$_{EV}$	R^2
F_1	−0.06	−0.05	5.08***	0.54**	0.28	92.67	0.00	0.00	5.15***	1.39***	0.64***	94.36
F_2	0.06	0.08	−0.02	0.41	0.20	−0.35	0.03	0.03	0.47***	0.09	0.34	7.86
F_3	0.05	0.05	0.16	−1.00***	−0.16	3.00	0.09	0.09	−0.47**	−1.55**	−0.85	8.06
F_4	0.13	0.04***	0.18***	−0.70***	2.22***	79.81	0.21	0.05***	0.27***	−0.94***	2.30***	83.81
F_5	0.03	0.02	0.07	0.28	−0.11	0.61	0.05	0.03	0.12	1.11***	0.59***	6.99
F_6	0.01	0.01	0.08	−0.04	0.25	0.58	0.10	0.04	−0.03	−0.38*	0.19	5.41
F_7	0.14	0.07***	0.09	0.58***	0.06	4.54	0.15	0.06**	0.14	0.43*	0.17	3.72
F_8	0.13	0.05**	0.02	1.56***	0.93***	27.05	0.18	0.05**	−0.06	1.38***	1.02***	28.80
F_9	0.02	0.01	−0.02	1.07***	0.65***	10.59	0.11	0.05*	−0.17***	1.25***	0.63***	14.71
F_{10}	−0.02	−0.01	0.03	0.22	0.13	0.08	−0.07	−0.02	−0.04	0.29*	0.08	0.38

Panel B: Tangency Portfolio Returns

	Full Sample						Post 20 Years					
	SR$_\alpha$	α	MKT	VAL$_{EV}$	MOM$_{EV}$	R^2	SR$_\alpha$	α	MKT	VAL$_{EV}$	MOM$_{EV}$	R^2
$\pi(F_{1-1})$	−0.06	0.00	0.27***	0.03**	0.01	92.67	0.00	0.00	0.29***	0.08***	0.04***	94.36
$\pi(F_{1-2})$	0.02	0.00	0.27***	0.05*	0.03	73.58	0.03	0.00	0.30***	0.08***	0.05***	89.30
$\pi(F_{1-3})$	0.04	0.00	0.28***	0.02	0.02	73.63	0.10	0.01	0.31***	−0.04	−0.01	77.32
$\pi(F_{1-4})$	0.12	0.01**	0.32***	−0.14***	0.54***	77.33	0.24	0.02***	0.39***	−0.29***	0.57***	83.78
$\pi(F_{1-5})$	0.12	0.01**	0.32***	−0.13***	0.54***	74.76	0.22	0.03***	0.40***	−0.11	0.69***	72.07
$\pi(F_{1-6})$	0.12	0.01**	0.33***	−0.13***	0.55***	75.78	0.23	0.04***	0.40***	−0.16*	0.65***	67.80
$\pi(F_{1-7})$	0.18	0.04***	0.36***	0.08	0.57***	46.65	0.26	0.06***	0.42***	0.10	0.72***	51.41
$\pi(F_{1-8})$	0.22	0.07***	0.37***	1.00***	1.12***	38.85	0.32	0.09***	0.41***	0.86***	1.19***	46.01
$\pi(F_{1-9})$	0.22	0.07***	0.36***	1.24***	1.26***	42.41	0.35	0.10***	0.39***	1.17***	1.40***	47.76
$\pi(F_{1-10})$	0.22	0.07***	0.36***	1.24***	1.27***	42.60	0.35	0.11***	0.39***	1.15***	1.38***	46.05

Table 4

Spanning Regressions of AMP Factors on Latent Factor Tangency Portfolios

The table presents OLS spanning regressions of each of the tradable factors of Asness et al. (2013) on the latent-factor tangency portfolio in the sense of Barillas and Shanken (2017). Specifically, we regress each of the three AMP factors — market (MKT), value (VAL_{EV}) and momentum (MOM_{EV}) — on the tangency portfolios comprising an increasing number of latent factors, $\pi(F_{1-k})$ for $k = 1, \ldots, 10$, plus a constant. The tangency portfolios are those estimated using RP-PCA with baseline RP-weight $\omega = 20$, and presented in Table 1. For each regression, we report the constant (α), the exposure (β), and the R^2 (in percent). Importantly, the α represents the part of the average excess return of the selected AMP factor unspanned by the tangency portfolio. A significant α means that the information in the AMP factor is not entirely subsumed by the tangency portfolio. We also report SR_α, i.e. the unexplained Sharpe ratio. The top panel covers the full sample (07/1983–12/2023), whereas the bottom panel uses only observations after the first 20 years (07/2003–12/2023). ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

		$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
Full Sample											
MKT	SR_α	0.07	0.04	0.03	0.02	0.02	0.02	0.00	0.01	0.02	0.02
	α	0.01*	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01
	β	3.41***	2.72***	2.68***	1.40***	1.39***	1.37***	0.96***	0.49***	0.43***	0.43***
	R^2	92.61	73.45	73.68	38.42	38.51	38.57	29.89	13.63	11.35	11.38
VAL_{EV}	SR_α	0.13	0.13	0.13	0.27	0.27	0.27	0.21	0.10	0.08	0.08
	α	0.03**	0.03**	0.03**	0.05***	0.05***	0.05***	0.04***	0.02	0.02	0.02
	β	0.05	0.06	0.03	−0.38***	−0.36***	−0.36***	−0.14***	0.04	0.07**	0.07**
	R^2	−0.05	0.08	−0.15	20.26	18.44	18.92	4.64	0.50	1.80	1.84
MOM_{EV}	SR_α	0.17	0.17	0.17	0.03	0.03	0.03	0.05	0.04	0.03	0.03
	α	0.04***	0.04***	0.04***	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	β	−0.28**	−0.22**	−0.20*	0.50***	0.47***	0.48***	0.24***	0.15***	0.15***	0.15***
	R^2	2.85	2.28	1.84	24.34	22.39	23.12	9.07	6.77	6.92	6.92
Post 20 Years											
		$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
MKT	SR_α	0.01	0.00	−0.01	−0.01	−0.01	−0.01	−0.03	−0.02	0.00	−0.01
	α	0.00	0.00	0.00	0.00	−0.01	−0.01	−0.01	−0.01	0.00	0.00
	β	3.22***	3.00***	2.52***	1.47***	1.25***	1.19***	0.97***	0.65***	0.55***	0.55***
	R^2	94.01	89.00	77.43	45.95	39.48	37.67	33.23	20.94	16.50	16.44
VAL_{EV}	SR_α	0.01	0.02	0.03	0.15	0.13	0.14	0.09	0.03	0.01	0.01
	α	0.00	0.00	0.00	0.02**	0.02	0.02	0.02	0.01	0.00	0.00
	β	0.24**	0.21**	0.12	−0.25***	−0.17***	−0.17***	−0.07	0.02	0.05	0.04
	R^2	4.88	3.96	1.42	12.66	7.33	7.61	1.27	−0.12	0.81	0.70
MOM_{EV}	SR_α	0.11	0.10	0.11	−0.04	−0.05	−0.04	−0.02	−0.05	−0.06	−0.06
	α	0.02*	0.02	0.02	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	β	−0.37**	−0.31**	−0.27**	0.33***	0.29***	0.27***	0.17***	0.15***	0.15***	0.15***
	R^2	7.21	5.69	5.01	14.28	13.38	11.99	5.85	6.64	7.52	7.09

Table 5
Tangency Portfolio Sharpe Ratio Decomposition

The table presents a decomposition of the Sharpe ratio (SR) of the optimal latent-factor tangency portfolio, π_{VM}, estimated by applying RP-PCA to the joint cross-section of the 48 value and momentum portfolios. Specifically, we decompose the SR into the spanned and unspanned components. The former is the component attributable to the combination of value and momentum "factors" extracted from separate cross-sections of test assets ($\pi_{V/M}$). The latter is the leftover, residual component, i.e., the residuals from regressing π_{VM} on $\pi_{V/M}$ plus the constant. Specifically, $\pi_{V/M}$ combines with mean–variance weights the two tangency portfolios computed separately on the 24 value (π_V) and 24 momentum test assets (π_M). That is, it is the tangency portfolio obtained from averaging over the two separate tangency portfolios. From left to right, the first two panels report the average excess returns ($\mathbb{E}$[R]), the standard deviation of the excess returns (σ[R]), the SR and the change in SR (ΔSR), resulting from adding an extra factor, for both the value, π_V, and momentum, π_M, tangency portfolios derived separately from the individual value and momentum test asset universes. The third panel contains the weights that each value (ω_V) and momentum (ω_M) portfolio take in $\pi_{V/M}$, and its statistics (expected return, volatility, and Sharpe ratio). For comparability, we scale all tangency portfolios such that the respective one-factor model has an annualized volatility of 10%. Finally, the fourth panel shows the decomposition of the Sharpe ratio of π_{VM} into the spanned (SR_S) and unspanned (SR_U) components. We perform the analysis using tangency portfolios π_j, for $j = \{V, M, V/M, VM\}$, which include an increasing number of factors up to the optimal number, i.e., F^j_{1-k} for $k = 1, 2, \ldots, 9$. We present the π_V and π_M tangency portfolios in Table IA.7, in the Internet Appendix.

	Value Tangency Portfolio (π_V)				Momentum Tangency Portfolio (π_M)				Combined Tangency Portfolio ($\pi_{V/M}$)						Spanning Regressions	
	$\mathbb{E}$[R]	σ[R]	SR	ΔSR	$\mathbb{E}$[R]	σ[R]	SR	ΔSR	ω_V	ω_M	$\mathbb{E}$[R]	σ[R]	SR	ΔSR	SR_S	SR_U
$\pi_j(F_{1-1})$	5.43	10.00	0.54	0.54	5.03	10.00	0.50	0.50	7.28	−6.28	6.46	10.00	0.65	0.65	0.23***	1.24***
$\pi_j(F_{1-2})$	6.37	10.83	0.59	0.04	7.23	11.99	0.60	0.10	0.14	0.86	2.70	4.47	0.60	−0.04	0.24***	1.23***
$\pi_j(F_{1-3})$	6.45	10.89	0.59	0.00	12.89	16.01	0.81	0.20	0.02	0.98	4.80	5.96	0.81	0.20	0.43***	1.04***
$\pi_j(F_{1-4})$	8.08	12.19	0.66	0.07	15.13	17.34	0.87	0.07	0.41	0.59	4.75	5.13	0.93	0.12	0.58***	0.89***
$\pi_j(F_{1-5})$	9.14	12.97	0.70	0.04	15.29	17.44	0.88	0.00	0.47	0.53	4.83	4.88	0.99	0.06	0.66***	0.81***
$\pi_j(F_{1-6})$	9.23	13.03	0.71	0.00	15.47	17.53	0.88	0.00	0.47	0.53	4.89	4.94	0.99	0.00	0.66***	0.81***
$\pi_j(F_{1-7})$	10.07	13.61	0.74	0.03	16.02	17.84	0.90	0.02	0.49	0.51	5.12	4.92	1.04	0.05	0.74***	0.73***
$\pi_j(F_{1-8})$	14.00	16.05	0.87	0.13	18.17	19.01	0.96	0.06	0.49	0.51	6.29	5.70	1.10	0.06	0.82***	0.66***
$\pi_j(F_{1-9})$	18.03	18.22	0.99	0.12	19.01	19.44	0.98	0.02	0.52	0.48	7.23	6.14	1.18	0.07	0.96***	0.51***

Table 6

Exposures of Candidate Factors to Latent Factors

The table presents the risk exposures of the candidate risk factors to the nine latent factors entering the optimal pricing kernel, estimated in the third-pass of the Giglio and Xiu (2021) procedure (Equation (9)). From Panels A to C, the candidate risk factors are grouped as follows: (A) the tangency portfolios and components of Table 5, (B) the *tradable* factors, and (C) the *non-tradable macro-financial* factors. Panel 1 shows the risk exposures, η_{F_k}, whereas Panel 2 reports the explained variation, R^2_{1-k} (in percent), for each F_k for $k = 1, \ldots, 9$. The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ (see Table 1). Tradable factors enter raw being returns, whereas non-tradable factors are expressed as innovations taken as residuals from an AR(1) process. For brevity, we only report the 34 tradable and nontradable candidate risk factors that have significant risk premia at the 5% level using the three-pass method. In Table IA.8, in the Internet Appendix, we present the estimates for the full list of candidate risk factors (roughly 100). We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987). The sample is monthly from 07/1983–12/2023.

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
	Panel A: Decomposition																	
R_{VM}	0.05***	0.06***	0.03***	0.24***	0.05***	0.05***	0.36***	0.59***	0.22***	12.69	15.57	15.92	30.68	31.34	31.82	51.03	92.80	100.00
R_S	0.08***	0.08***	0.04***	0.15***	0.04***	0.02***	0.30***	0.26***	−0.07***	40.54	48.22	49.39	58.45	59.29	59.40	80.13	92.86	93.83
R_U	−0.02***	−0.02***	−0.01	0.09***	0.01	0.03***	0.06***	0.32***	0.29***	7.58	8.18	8.09	13.71	13.57	13.93	15.17	52.39	88.07
R_V	0.06***	0.04***	0.01**	−0.06***	0.04***	−0.01	0.33***	0.21***	−0.01	30.23	33.82	33.98	36.21	37.19	37.13	72.27	84.20	84.22
R_M	0.05***	0.06***	0.04***	0.27***	0.02***	0.04***	0.09***	0.15***	−0.08***	26.44	33.85	35.53	80.45	80.71	81.72	84.34	90.54	92.67
	Panel B: Tradable																	
fxcar	0.12***	0.16***	−0.13***	−0.09	0.09	0.10	0.01	0.10	0.07	12.07	16.33	17.79	17.98	18.27	18.50	18.32	18.35	18.29
eqstrad	−0.11***	−0.05	−0.02	−0.04	−0.28***	0.09	0.12	−0.19	−0.07	10.29	10.19	9.94	9.76	13.00	13.10	13.05	13.50	13.37
bdstrad	−0.11***	−0.08	−0.04	0.02	−0.10	0.02	0.02	−0.29**	−0.14	9.12	9.53	9.41	9.19	9.58	9.35	9.11	10.47	10.69
comstrad	−0.06**	−0.13**	−0.07	0.21***	−0.12	0.02	−0.10	−0.22*	−0.06	3.54	5.06	5.23	7.65	8.07	7.81	7.91	8.63	8.46
jkpdebiss	−0.03*	−0.10**	0.00	0.11	−0.04	0.13	−0.22**	−0.15	−0.06	0.83	2.22	2.00	2.43	2.31	2.69	3.73	4.02	3.88
Panel C: Non-tradable Macro-Financial																		
	Panel C1: Financial Uncertainty																	
gfc	0.33***	0.12***	−0.16***	−0.15***	0.13***	0.11***	−0.10***	0.08*	−0.05	79.11	81.36	83.86	84.98	85.94	86.47	86.68	86.79	86.82
vix/vxo	−0.22***	−0.13***	−0.04	0.01	−0.22***	−0.03	−0.11	0.00	0.06	40.77	43.38	43.38	43.27	45.79	45.72	45.91	45.79	45.78
impvar	−0.21***	−0.08**	−0.01	0.04	−0.18*	−0.01	−0.34***	−0.13	0.09	40.18	40.38	40.20	40.19	41.02	40.97	43.50	43.81	43.83
avgcor	−0.13***	−0.09***	−0.06	−0.09	−0.17***	0.00	0.12	−0.22**	−0.12	14.09	15.26	15.46	15.69	17.24	17.07	17.29	18.20	18.38
finunc	−0.12***	−0.06**	0.06	0.12*	−0.19***	−0.10	−0.02	−0.12	−0.02	12.16	12.60	12.80	13.28	15.23	15.51	15.34	15.46	15.29
emvfincri	−0.10**	−0.04	0.06	0.00	−0.13*	0.05	0.04	−0.18*	−0.21**	8.56	8.62	8.90	8.71	9.49	9.38	9.23	9.75	10.70
move	−0.12***	−0.03	−0.07*	−0.10	−0.02	−0.06	−0.13	−0.12	−0.01	10.28	10.21	10.55	10.82	10.64	10.58	10.80	10.89	10.69
ted	−0.09***	−0.08**	−0.07	−0.14**	−0.05	−0.15	0.02	−0.12	−0.05	6.67	7.60	7.89	8.73	8.65	9.42	9.21	9.33	9.17
fsi	−0.10***	0.02	0.00	−0.02	−0.14**	−0.11*	−0.02	−0.05	0.02	7.19	7.01	6.79	6.56	7.64	8.02	7.80	7.62	7.39

(*continued over page*)

Table 6 — Continued

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
Panel C2: Liquidity																		
icap	0.24***	0.18***	0.12***	−0.31***	0.28***	0.19***	0.09	0.02	−0.14**	45.55	50.33	51.81	56.36	61.07	62.45	62.57	62.50	62.94
Panel C3: Crash Risk																		
adbear	−0.26***	−0.13***	−0.13***	−0.03	−0.23***	−0.15	−0.09	−0.12	−0.02	57.40	58.22	60.10	59.98	62.30	62.79	62.92	63.08	62.92
skew	0.07***	0.06**	0.12**	0.06	0.02	0.09	0.01	0.21**	−0.04	3.64	4.04	5.57	5.54	5.38	5.54	5.34	6.08	5.93
Panel C4: Macro																		
ygap	−0.15***	−0.10***	−0.21***	0.03	−0.08**	−0.10	−0.45***	0.03	0.12	17.74	19.25	24.12	24.00	24.25	24.47	29.69	29.56	29.79
emvov	−0.14***	−0.06	−0.06	−0.04	−0.18***	−0.03	0.19*	−0.11	−0.18*	15.76	16.27	16.46	16.35	18.08	17.95	18.69	18.80	19.47
emvout	−0.13***	−0.06*	−0.07	−0.04	−0.17***	−0.03	0.19*	−0.11	−0.22**	14.33	14.85	15.17	15.05	16.65	16.50	17.18	17.28	18.33
emvinf	−0.12***	−0.07*	−0.15**	−0.02	−0.13***	0.00	0.15*	−0.03	−0.14	10.87	11.44	13.81	13.64	14.45	14.26	14.65	14.49	14.84
dei	−0.02	0.03	−0.04	−0.03	0.03	0.12*	−0.07	−0.19*	−0.11	0.34	0.21	0.19	0.03	−0.15	0.22	0.11	0.63	0.73
Panel C5: Interest Rate & Monetary Policy																		
ltychg	0.00	0.02	−0.19***	−0.31***	0.26***	−0.21***	−0.62***	−0.38***	0.09	0.00	−0.15	3.69	8.19	12.05	13.65	23.66	26.65	26.71
emvmon	−0.14***	−0.04	−0.05	−0.06	−0.15***	−0.01	0.23**	−0.16*	−0.26***	16.50	16.55	16.64	16.67	17.88	17.71	18.82	19.23	20.80
emvir	−0.13***	−0.07*	−0.11**	−0.09	−0.13**	−0.06	0.17	−0.10	−0.12	13.36	14.03	15.20	15.44	16.18	16.15	16.73	16.76	16.93
trms	−0.02	−0.03	−0.10*	−0.28***	0.10	−0.22***	−0.29***	−0.22**	−0.04	0.28	0.20	1.16	4.74	5.15	6.96	8.98	9.81	9.66
uts	0.00	−0.01	−0.17***	−0.19***	0.21***	−0.01	−0.26***	−0.23*	0.18*	0.00	−0.21	2.38	3.61	6.23	6.01	7.79	8.66	9.32
mpbsort	−0.10***	−0.02	0.03	−0.01	−0.02	−0.14	−0.08	−0.10	0.07	7.14	6.91	6.76	6.52	6.29	6.73	6.65	6.61	6.47
mpbs	−0.07***	0.00	−0.04	0.01	0.04	−0.16	−0.28*	−0.14	0.14	2.38	2.13	1.98	1.75	1.57	2.30	4.03	4.17	4.37
mjsummp	−0.03*	0.01	0.00	−0.09	0.11	−0.23*	−0.20	−0.19*	0.09	0.45	0.29	0.03	0.26	0.54	1.90	2.57	3.17	3.13
mjodysu2	−0.06***	0.06	0.02	−0.04	0.02	−0.04	−0.17	−0.07	0.03	2.28	2.58	2.36	2.19	1.97	1.83	2.30	2.17	1.93
Panel C6: Political Uncertainty																		
emvpol	−0.14***	−0.04	−0.07	−0.03	−0.18***	−0.06	0.24**	−0.11	−0.21**	14.66	14.80	15.18	15.04	16.66	16.62	17.95	18.03	18.97
Panel C7: Behavioral																		
dtoat	0.28***	0.20***	0.18***	−0.05	0.27***	0.24***	0.24***	−0.06	−0.15***	60.45	66.83	70.50	70.58	74.97	77.38	78.90	78.93	79.48
dtoy	0.27***	0.19***	0.15***	−0.03	0.25***	0.18***	0.25***	−0.08	−0.09*	59.55	65.29	67.75	67.74	71.43	72.67	74.31	74.40	74.57

Table 7
Risk Premia of Candidate Factors

The table presents the risk premium estimates obtained with the three-pass method of Giglio and Xiu (2021) (Equation (10a)). From Panels A to C, the candidate risk factors are grouped as follows: (A) the tangency portfolios and components of Table 5, (B) the *tradable* factors, and (C) the *non-tradable macro-financial* factors. Panel 1 shows the risk premium estimates (λ), whereas Panel 2 reports the Sharpe ratio of the de-noised candidate risk factor. We report the estimates using models including an increasing number of latent factors, F_{1-k} for $k = 1, 2, \ldots, 9$. The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ (see Table 1). Tradable factors are returns and therefore enter raw, whereas non-tradable factors are expressed as innovations taken as residuals from an AR(1) process. For brevity, we only report the 34 tradable and nontradable candidate risk factors that have significant risk premia at the 5% level. In Table IA.9, in the Internet Appendix, we present the estimates for the full list of candidate risk factors (roughly 100). We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated as in Giglio and Xiu (2021). The sample is monthly from 07/1983–12/2023.

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$SR_{F_{1-1}}$	$SR_{F_{1-2}}$	$SR_{F_{1-3}}$	$SR_{F_{1-4}}$	$SR_{F_{1-5}}$	$SR_{F_{1-6}}$	$SR_{F_{1-7}}$	$SR_{F_{1-8}}$	$SR_{F_{1-9}}$
Panel A: Decomposition																		
R_{VM}	2.29***	2.84***	2.93***	5.61***	5.75***	5.86***	9.31***	16.75***	18.03***	0.52	0.58	0.59	0.82	0.83	0.84	1.06	1.42	1.47
R_S	3.32***	4.03***	4.15***	5.85***	5.98***	6.03***	8.93***	12.26***	11.88***	0.52	0.58	0.59	0.77	0.78	0.78	1.00	1.28	1.23
R_U	−1.03**	−1.20***	−1.22***	−0.25	−0.23	−0.17	0.38	4.48***	6.15***	0.52	0.58	0.59	0.09	0.08	0.06	0.13	0.86	0.91
R_V	2.38***	2.78***	2.83***	2.12**	2.23**	2.21**	5.34***	8.01***	7.95***	0.52	0.58	0.59	0.42	0.44	0.44	0.76	1.06	1.05
R_M	2.20***	2.77***	2.89***	5.98***	6.04***	6.13***	6.98***	8.89***	8.43***	0.52	0.58	0.59	0.82	0.82	0.83	0.93	1.15	1.07
Panel B: Tradable																		
bdstrad	−4.57**	−5.13**	−5.31**	−5.03**	−5.29**	−5.20**	−5.41**	−8.99***	−9.85***	0.52	0.58	0.59	0.56	0.57	0.56	0.59	0.88	0.93
jkpdebiss	−1.36*	−2.28**	−2.28**	−0.99	−1.10	−0.83	−3.00	−4.94*	−5.25**	0.52	0.51	0.51	0.20	0.22	0.15	0.47	0.73	0.77
eqstrad	−4.85***	−5.12***	−5.13***	−5.56***	−6.17***	−5.86***	−5.01**	−7.36**	−7.79**	0.52	0.56	0.56	0.60	0.57	0.53	0.46	0.65	0.68
comstrad	−2.84**	−3.77**	−4.09**	−1.50	−1.77	−1.75	−2.92	−5.71**	−6.08**	0.52	0.56	0.57	0.18	0.20	0.20	0.33	0.61	0.64
fxcar	5.29***	6.85***	6.46***	5.46**	5.70**	5.94***	6.05**	7.27***	7.61***	0.52	0.58	0.52	0.44	0.45	0.47	0.47	0.57	0.59
Panel C: Non-tradable Macro-Financial																		
Panel C1: Financial Uncertainty																		
move	−4.90***	−5.19***	−5.47***	−6.63***	−6.70***	−6.88***	−8.15***	−9.69***	−9.76***	0.52	0.55	0.56	0.66	0.67	0.68	0.79	0.92	0.92
ted	−3.92**	−4.68***	−4.89***	−6.54***	−6.68***	−7.05***	−6.93***	−8.46***	−8.71***	0.52	0.58	0.59	0.74	0.75	0.75	0.74	0.89	0.92
avgcor	−5.68***	−6.54***	−6.73***	−7.77***	−8.27***	−8.27***	−7.10***	−9.92***	−10.58***	0.52	0.58	0.59	0.67	0.68	0.68	0.57	0.78	0.82
emvfincri	−4.40**	−4.77**	−4.57**	−4.59**	−4.97**	−4.85**	−4.47	−6.77*	−7.95**	0.52	0.56	0.52	0.52	0.54	0.53	0.48	0.71	0.79
impvar	−9.38***	−9.79***	−9.78***	−9.11**	−9.39**	−9.60**	−12.79***	−14.75***	−14.17***	0.52	0.55	0.55	0.51	0.54	0.54	0.71	0.80	0.77
fsi	−4.11***	−3.93**	−3.95**	−4.13**	−4.53**	−4.88**	−5.11**	−5.70**	−5.62**	0.52	0.50	0.50	0.53	0.53	0.55	0.57	0.64	0.63
vix/vxo	−9.57***	−10.77***	−10.87***	−10.70***	−11.34***	−11.42***	−12.50***	−12.44***	−12.08***	0.52	0.57	0.58	0.57	0.59	0.59	0.64	0.64	0.62
finunc	−5.28***	−5.87***	−5.68***	−4.35**	−4.91**	−5.13**	−5.28**	−6.75***	−6.85***	0.52	0.57	0.54	0.41	0.43	0.44	0.45	0.57	0.58
gfc	13.86***	15.01***	14.63***	12.88***	13.22***	13.54***	12.57***	13.57***	13.33***	0.52	0.56	0.53	0.46	0.47	0.48	0.45	0.48	0.48
Panel C2: Liquidity																		
icap	10.22***	11.86***	12.24***	8.72**	9.55**	9.96**	10.78***	11.06***	10.25**	0.52	0.58	0.59	0.40	0.42	0.43	0.47	0.48	0.44

(*continued over page*)

Table 7 — Continued

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$\text{SR}_{F_{1-1}}$	$\text{SR}_{F_{1-2}}$	$\text{SR}_{F_{1-3}}$	$\text{SR}_{F_{1-4}}$	$\text{SR}_{F_{1-5}}$	$\text{SR}_{F_{1-6}}$	$\text{SR}_{F_{1-7}}$	$\text{SR}_{F_{1-8}}$	$\text{SR}_{F_{1-9}}$
	Panel C3: Crash Risk																	
skew	2.89*	3.46**	3.87**	4.53**	4.60**	4.80**	4.86**	7.49***	7.26***	0.52	0.58	0.55	0.63	0.64	0.65	0.66	0.95	0.92
adbear	−11.24**	−11.83**	−12.52**	−12.86**	−13.13**	−13.86**	−14.99**	−16.46***	−16.57***	0.52	0.56	0.57	0.58	0.60	0.61	0.66	0.72	0.72
	Panel C4: Macro																	
dei	−0.91	−0.67	−0.78	−1.23	−1.14	−0.80	−1.53	−3.82*	−4.40**	0.52	0.35	0.34	0.50	0.45	0.24	0.44	0.90	0.97
ygap	−6.38***	−7.34***	−8.02***	−7.72***	−7.96***	−8.17***	−12.45***	−12.06***	−11.37***	0.52	0.58	0.56	0.54	0.55	0.56	0.78	0.75	0.71
emvout	−5.70***	−6.30***	−6.51***	−6.92***	−7.43***	−7.50***	−5.73**	−7.16***	−8.39***	0.52	0.57	0.58	0.61	0.62	0.63	0.47	0.58	0.66
emvov	−5.98***	−6.58***	−6.76***	−7.19***	−7.72***	−7.80***	−5.97**	−7.43***	−8.45***	0.52	0.57	0.58	0.61	0.62	0.63	0.47	0.58	0.64
emvinf	−4.96***	−5.59***	−6.07***	−6.28***	−6.66***	−6.67***	−5.22**	−5.60**	−6.41***	0.52	0.57	0.56	0.58	0.60	0.60	0.46	0.49	0.55
	Panel C5: Interest Rate & Monetary Policy																	
trms	−0.80	−1.07	−1.40	−4.57**	−4.28**	−4.75**	−7.50***	−10.24***	−10.45***	0.52	0.58	0.39	0.69	0.61	0.58	0.82	1.06	1.08
ltychg	0.06	0.24	−0.38	−3.92*	−3.16	−3.60	−9.49***	−14.31***	−13.79***	0.52	0.34	0.06	0.46	0.31	0.33	0.66	0.94	0.90
mjsummp	−1.03	−0.81	−0.81	−1.94	−1.67	−2.31	−4.15**	−6.76***	−6.21**	0.52	0.36	0.36	0.64	0.41	0.37	0.65	0.94	0.86
mpbs	−2.45**	−2.38*	−2.48*	−2.18	−2.09	−2.75*	−5.67***	−7.43***	−6.69**	0.52	0.51	0.52	0.46	0.43	0.45	0.75	0.95	0.83
mjodysu2	−2.32**	−1.78	−1.71	−2.18	−2.12	−2.29	−3.91**	−4.88**	−4.72**	0.52	0.35	0.34	0.42	0.40	0.42	0.67	0.82	0.80
mpbsort	−4.25***	−4.35***	−4.25***	−4.32**	−4.36**	−4.91**	−5.77***	−7.03***	−6.67**	0.52	0.53	0.52	0.53	0.53	0.55	0.64	0.76	0.72
emvmon	−6.11***	−6.46***	−6.62***	−7.36***	−7.81***	−7.83***	−5.67**	−7.77***	−9.23***	0.52	0.55	0.56	0.62	0.63	0.63	0.44	0.60	0.68
uts	−0.08	−0.20	−0.60	−2.56	−1.98	−1.99	−4.78**	−7.55***	−6.63**	0.52	0.43	0.12	0.42	0.25	0.25	0.53	0.81	0.68
emvir	−5.50***	−6.17***	−6.52***	−7.57***	−7.94***	−8.09***	−6.42***	−7.68***	−8.34***	0.52	0.57	0.58	0.66	0.67	0.68	0.53	0.63	0.68
	Panel C6: Political Uncertainty																	
emvpol	−5.76***	−6.17***	−6.40***	−6.75***	−7.27***	−7.41***	−5.06**	−6.45**	−7.62***	0.52	0.56	0.57	0.60	0.61	0.62	0.40	0.51	0.59
	Panel C7: Behavioral																	
dtoy	11.68***	13.47***	13.96***	13.57***	14.31***	14.69***	17.10***	16.09***	15.55***	0.52	0.58	0.59	0.57	0.58	0.60	0.68	0.64	0.62
dtoat	11.77***	13.66***	14.25***	13.63***	14.42***	14.95***	17.26***	16.51***	15.64***	0.52	0.58	0.59	0.56	0.58	0.59	0.67	0.64	0.61

Table 8
Macro-Financial Risk Factors and the Tangency Portfolio

The table presents univariate spanning regressions of the optimal tangency portfolio return (R_{VM}; left panels), the spanned component (R_S; mid panels), and the unspanned component (R_U; right panels) on the priced macro-financial risk factors. For each panel, we report the constant, α, the regression coefficient, β, and the explained variation, R^2 (in percent). The tangency portfolio, its components and the candidate risk factors entering the regressions are first de-noised using the three-pass method, so that all variables are return-based. This implies that the αs are meaningful objects to assess, in the sense of Barillas and Shanken (2017). For brevity, we only report the 34 tradable and nontradable candidate risk factors that have significant risk premia at the 5% level using the three-pass method. In Table IA.10, in the Internet Appendix, we present the estimates for the full list of roughly 100 candidate risk factors. We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * correspond to a rejection of the null hypothesis of zero at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

	α_{VM}	β_{VM}	R^2_{VM}	α_S	β_S	R^2_S	α_U	β_U	R^2_U
				Panel A: Tradable					
bdstrad	0.11***	−0.73***	39.90	0.05***	−0.68***	55.95	0.06***	−0.05	0.62
jkpdebiss	0.13***	−0.95***	27.54	0.07***	−0.89***	39.07	0.06***	−0.06	0.36
eqstrad	0.14***	−0.50***	21.53	0.08***	−0.52***	37.82	0.06***	0.02	0.13
comstrad	0.15***	−0.57***	19.22	0.08***	−0.59***	33.76	0.06***	0.02	0.12
fxcar	0.15***	0.38***	16.24	0.08***	0.47***	39.46	0.07***	−0.09*	2.77
				Panel B: Non-tradable Macro-Financial					
				Panel B1: Financial Uncertainty					
move	0.11***	−0.73***	39.55	0.04***	−0.79***	75.17	0.07***	0.06	0.94
ted	0.11***	−0.81***	38.92	0.05***	−0.81***	63.80	0.06***	0.01	0.01
avgcor	0.12***	−0.54***	31.44	0.06***	−0.55***	52.63	0.06***	0.01	0.03
emvfincri	0.13***	−0.65***	28.83	0.07***	−0.59***	38.46	0.06***	−0.06	0.80
impvar	0.13***	−0.35***	27.57	0.06***	−0.44***	69.16	0.07***	0.09***	5.55
fsi	0.15***	−0.59***	18.26	0.08***	−0.73***	45.20	0.07***	0.14**	3.43
vix/vxo	0.15***	−0.26***	17.72	0.07***	−0.37***	56.85	0.07***	0.11***	9.86
finunc	0.15***	−0.41***	15.57	0.08***	−0.52***	40.42	0.07***	0.11**	3.70
gfc	0.16***	0.14***	10.45	0.09***	0.21***	38.88	0.07***	−0.07***	9.31
				Panel B2: Liquidity					
icap	0.16***	0.16***	9.15	0.09***	0.27***	41.49	0.07***	−0.11***	13.88
				Panel B3: Crash Risk					
skew	0.11***	0.97***	39.01	0.05***	0.98***	64.01	0.06***	−0.01	0.01
adbear	0.14***	−0.26***	23.93	0.07***	−0.32***	59.65	0.07***	0.06**	4.67
				Panel B4: Macro					
dei	0.10***	−1.78***	43.41	0.07***	−1.01***	22.66	0.03***	−0.77***	26.86
ygap	0.14***	−0.37***	23.12	0.06***	−0.49***	66.02	0.08***	0.12***	8.35
emvout	0.14***	−0.43***	19.87	0.08***	−0.45***	35.42	0.06***	0.02	0.17
emvov	0.15***	−0.41***	19.12	0.08***	−0.45***	36.94	0.06***	0.04	0.56
emvinf	0.15***	−0.40***	14.11	0.09***	−0.48***	33.54	0.07***	0.08*	2.13
				Panel B5: Interest Rate & Monetary Policy					
trms	0.08***	−0.94***	54.25	0.05***	−0.66***	43.68	0.03***	−0.28***	15.58
ltychg	0.11***	−0.49***	37.70	0.07***	−0.34***	29.07	0.04***	−0.15***	11.97
mjsummp	0.12***	−1.00***	34.37	0.07***	−0.84***	39.53	0.05***	−0.16***	2.78
mpbs	0.12***	−0.86***	31.94	0.05***	−0.97***	65.33	0.07***	0.11**	1.67
mjodysu2	0.13***	−1.12***	29.25	0.06***	−1.15***	49.70	0.06***	0.03	0.06
mpbsort	0.14***	−0.65***	24.15	0.07***	−0.80***	58.96	0.07***	0.15**	4.22
emvmon	0.14***	−0.42***	21.35	0.08***	−0.41***	33.19	0.06***	−0.01	0.03
uts	0.14***	−0.58***	21.15	0.09***	−0.48***	23.33	0.05***	−0.10**	2.12
emvir	0.14***	−0.46***	21.15	0.08***	−0.51***	42.55	0.07***	0.05	0.95
				Panel B6: Political Uncertainty					
emvpol	0.15***	−0.37***	15.85	0.09***	−0.40***	29.61	0.06***	0.03	0.30
				Panel B7: Behavioral					
dtoy	0.15***	0.21***	17.86	0.07***	0.30***	58.75	0.08***	−0.09***	10.83
dtoat	0.15***	0.20***	16.97	0.07***	0.28***	57.64	0.08***	−0.09***	11.42

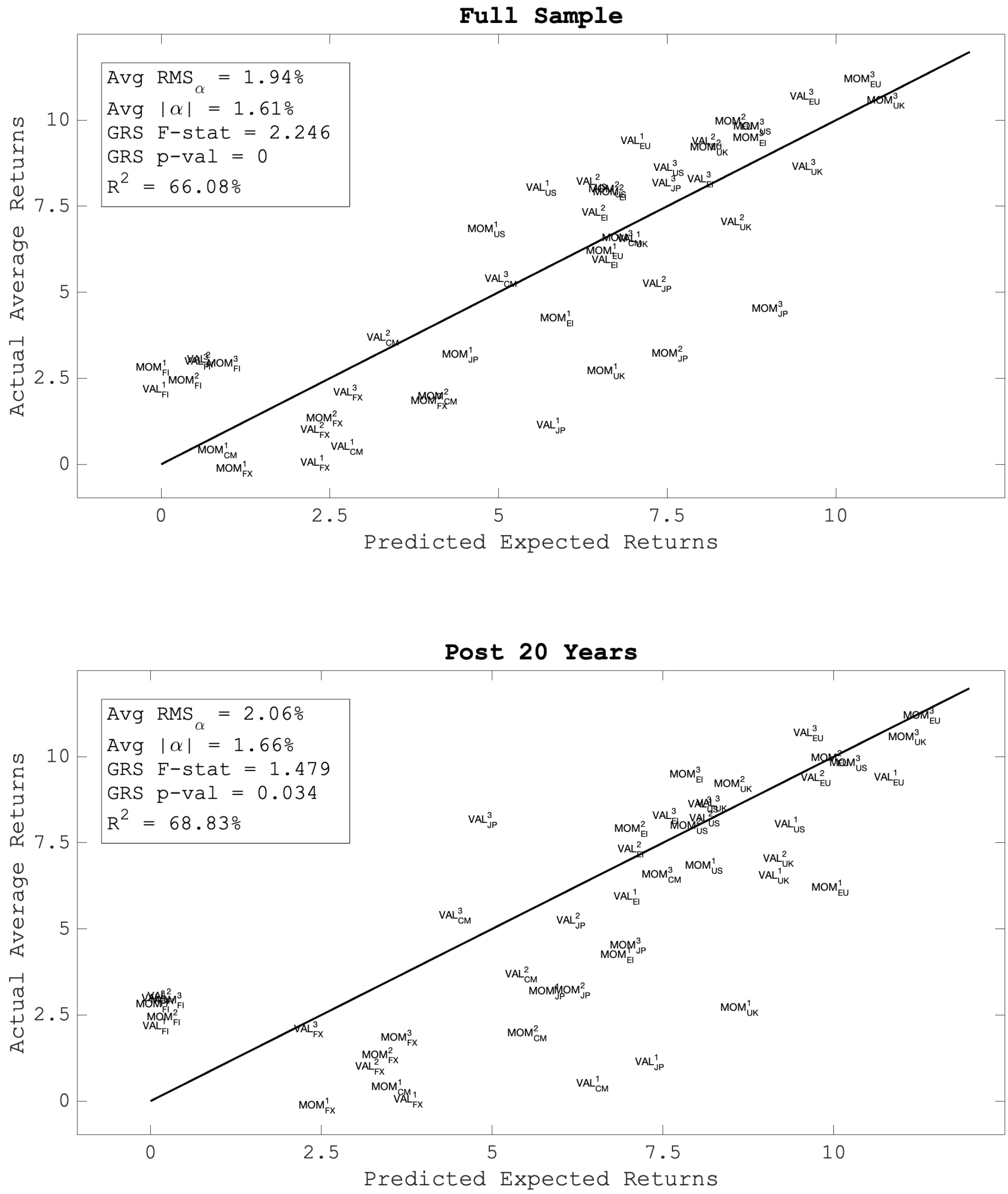
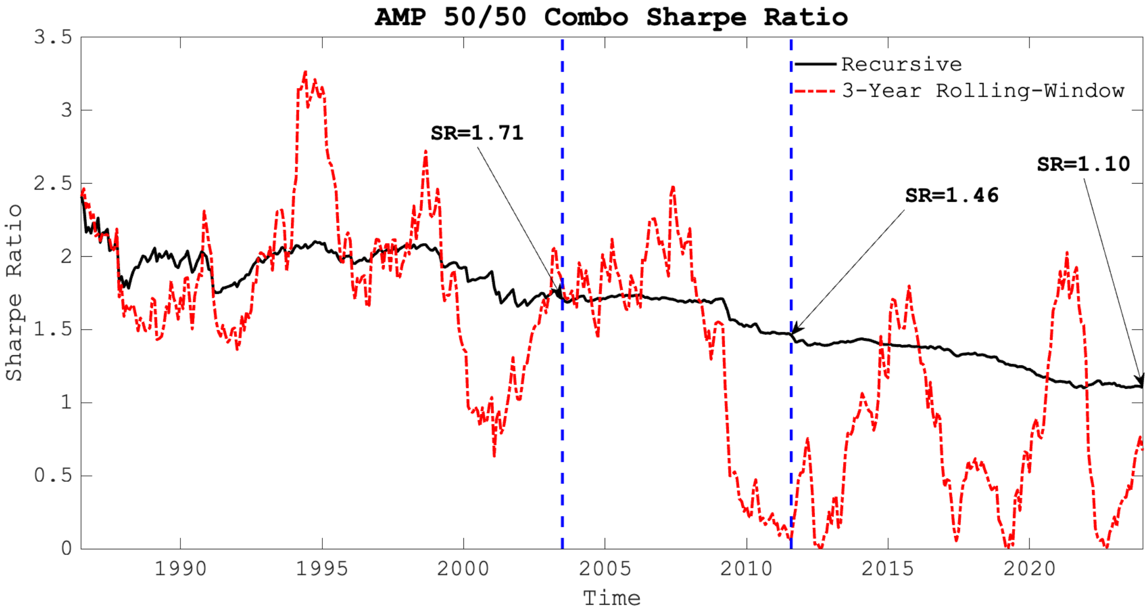


Figure 1. Pricing the Cross-section of Value and Momentum Portfolios with the AMP Model. The figure presents Fama and MacBeth (1973) asset pricing tests of the three-factor model of Asness et al. (2013) on the cross-section of 48 value and momentum portfolios. The AMP model includes the market, and value and momentum 'everywhere' factors. The figure shows the actual average returns versus the model-implied expected returns (fitted-values from the cross-sectional regression). The upper (lower) panel reports the model fit over the period 07/1983–12/2023 (07/2002–12/2023), at monthly frequency. The solid line is a 45° line to highlight the model fit. Each panel also reports: the average root-mean-square pricing error ($Avg\ RMS_\alpha$), the average absolute alpha ($Avg\ |\alpha|$), the F-statistic and p-value from the Gibbons et al. (1989) test, and the cross-sectional explained variation (R^2), in percent.



AMP 50/50 Combo Sharpe Ratio

Sample	Sharpe Ratio
1983–2023	1.10
1983–2003	1.71
2003–2023	0.44
2011–2023	0.21

Figure 2. The Performance of the AMP 50/50 Combo Overtime. The figure presents the performance of the 50/50 value–momentum combo strategy of Asness et al. (2013) over the period 07/1983–12/2023. The strategy combines the value and momentum 'everywhere' factors of AMP with equal weights. The plot displays the recursive (solid black) and 3-year rolling-window (dashed red) Sharpe ratio estimates. The recursive estimates use an initial window of 3 years. Thus, the first estimates start in 06/1986. The table below reports the Sharpe ratios over a range of sample periods, including: (i) the full sample (07/1983–12/2023), (ii) the first 20 years (07/1983–06/2003), (iii) the post-20 years (07/2003–12/2023), and (iv) the last 12 years following the end of AMP's original sample period (08/2011–12/2023).

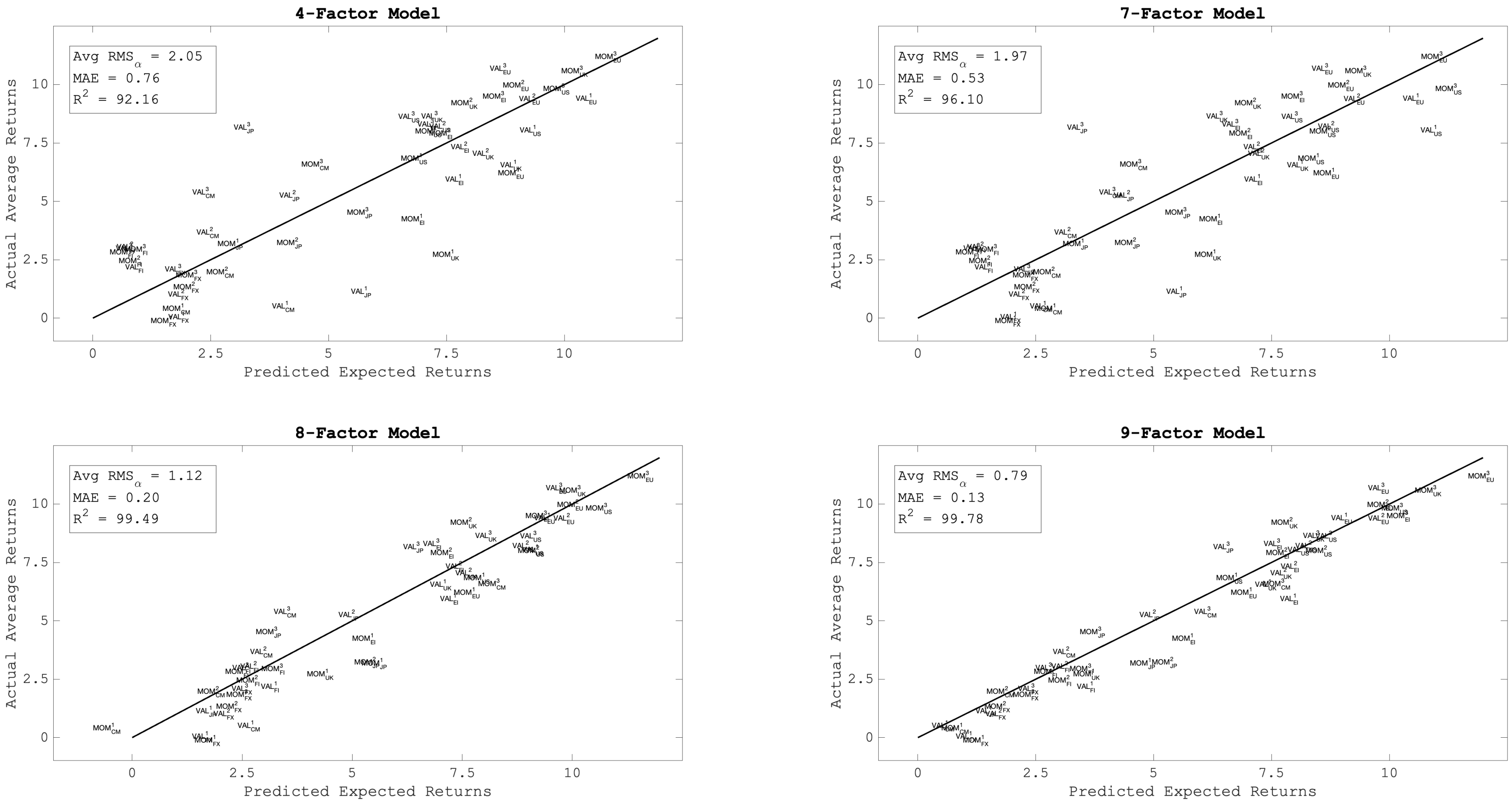


Figure 3. Pricing the Cross-Section of Value and Momentum Portfolios with the Latent-Factor Models. The figure shows how four latent-factor models with increasing numbers of latent factors (four, seven, eight and nine, respectively) perform when used to price the cross-section of value and momentum portfolios. The latent factors are estimated by applying RP-PCA with baseline RP-weight ($\omega = 20$) to the 48 portfolios (Table 1 shows additional properties of these models). The figure shows the actual average returns versus the model-implied expected returns (fitted-values from the cross-sectional regression). We plot the 45° line to highlight the model fit. Each panel also reports: the average root-mean-square pricing error from the first-pass ($Avg\ RMS_\alpha$), the mean absolute error from the second-pass (MAE), and the cross-sectional explained variation (R^2), in percent. The sample is monthly, from 07/1983–12/2023.

Figure 4. Stability Analysis of the Latent-Factor Models. The figure shows recursive estimates of the Sharpe ratios of tangency portfolios incorporating an increasing number of latent factors. Specifically, we estimate the latent factors by applying RP-PCA with baseline RP-weight ($\omega = 20$) to the cross-section of the 48 value and momentum test assets over the 07/1983–12/2023 period. The tangency portfolios are: $\pi(F_{1-k})$ for $k = 1, \ldots, 10$. The tangency portfolio weights of the latent factors are given by the inverse of the covariance matrix (diagonal, as the latent factors are orthogonal) multiplied by factor means ($\widehat{b} = \mu_F \Sigma_F^{-1}$); see Table 1. We use an initial expanding window of 20 years, so that the Sharpe ratios displayed cover the 07/2003–12/2023 period.

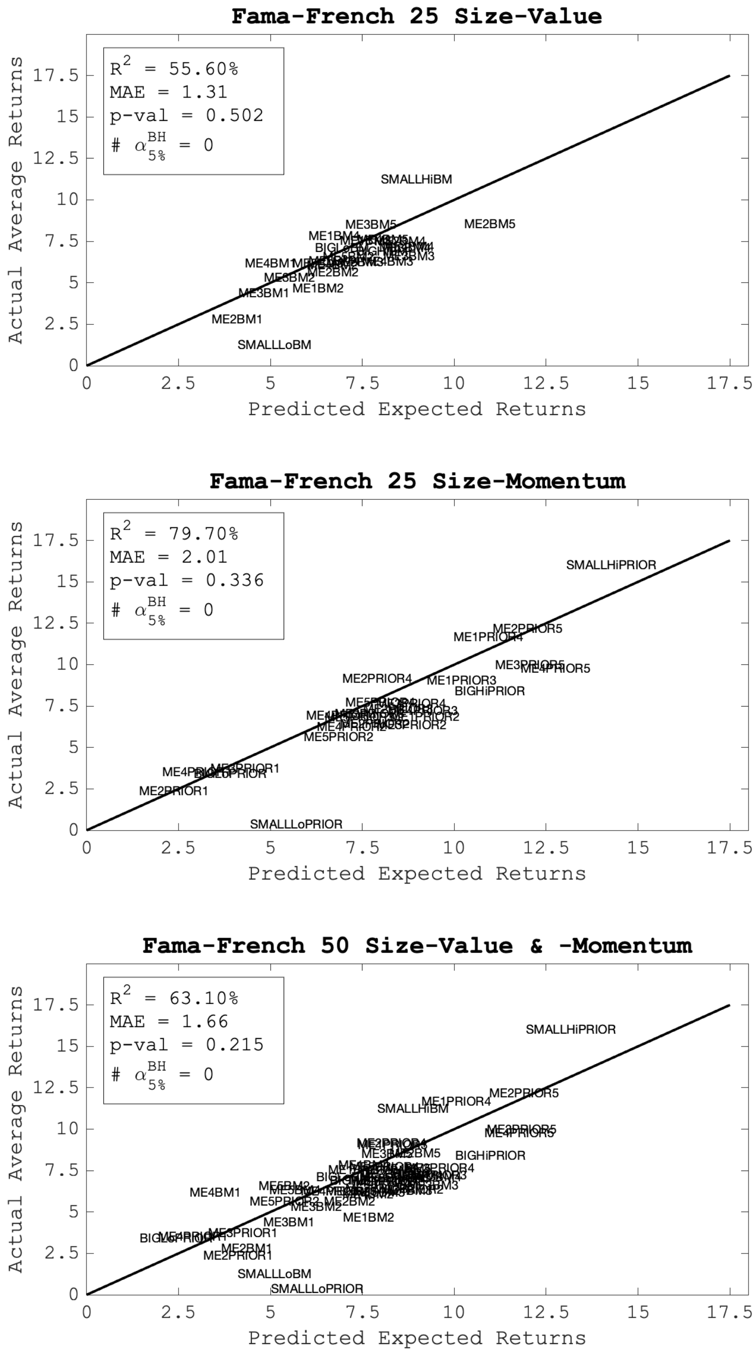


Figure 5. Out-of-Sample Cross-sectional Pricing Performance of the Latent-Factor Model. The figure shows how the optimal latent-factor model performs when used to price three cross-sections of Fama-French's test assets. The optimal model includes nine factors estimated with baseline RP-weight (see Table 1). The three cross-sections are: (i) 25 developed-market Size-Value portfolios (top panel); (ii) 25 developed-market Size-Momentum portfolios (middle panel); and, (iii) the combination of the 25 Size-Value and 25 Size-Momentum portfolios (bottom panel). All test assets are in excess of the developed-market risk-free rate. The analysis is out-of-sample in the sense that these test assets are not used to estimate the latent factors. The figure shows the actual average returns versus the model-implied expected returns (fitted-values from the cross-sectional regression). A 45° line is plotted through the origin, to highlight model fit. Each panel also reports: the cross-sectional explained variation (R^2) in percent, the mean absolute pricing error (MAE) and p-value (p-val) from the second-pass, and the number of individually statistically significant alphas at the Benjamini and Hochberg (1995, BH) 5% level ($\# \alpha_{5\%}^{BH}$). The statistical significance of all pricing errors is estimated using a wild bootstrap procedure similar to that of Giglio et al. (2021); see Section IA.2.3, in the Internet Appendix, for details of the wild bootstrap algorithm. The sample is from 07/1983–12/2023, at monthly frequency.

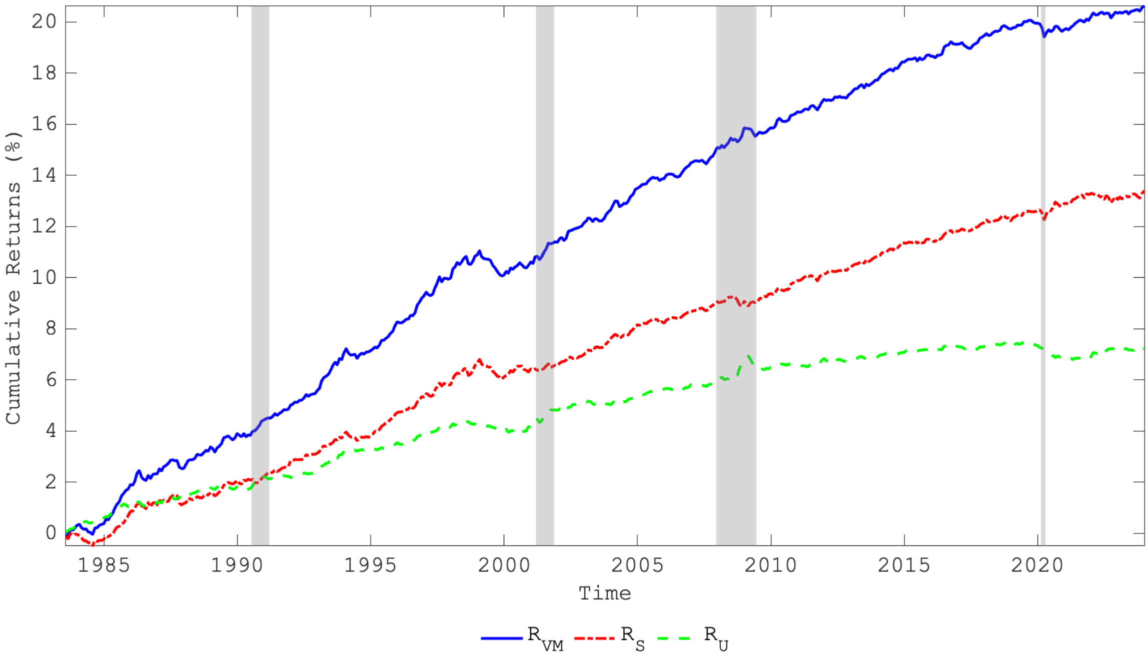


Figure 6. Decomposing the Optimal Tangency Portfolio Returns. The figure shows the cumulative sum of the (log) returns of the nine-latent-factor tangency portfolio (R_{VM}), and its spanned (R_S) and unspanned (R_U) components. The latent factors are estimated by applying RP-PCA with baseline RP-weight ($\omega = 20$) to the 48 value and momentum portfolios (see Table 1). The components are obtained by regressing R_{VM} on $R_{V/M}$, i.e., the tangency portfolio constructed by combining the separate value and momentum tangency portfolios. These portfolios are extracted by applying RP-PCA to the two separate value and momentum cross-sections, each consisting of 24 test assets (see Table 5). To improve interpretability, we scale all tangency portfolios so that the annualized volatility of R_{VM} is 10%. The shaded gray areas are NBER recession periods. The sample is monthly and covers the 07/1983-12/2023 period.

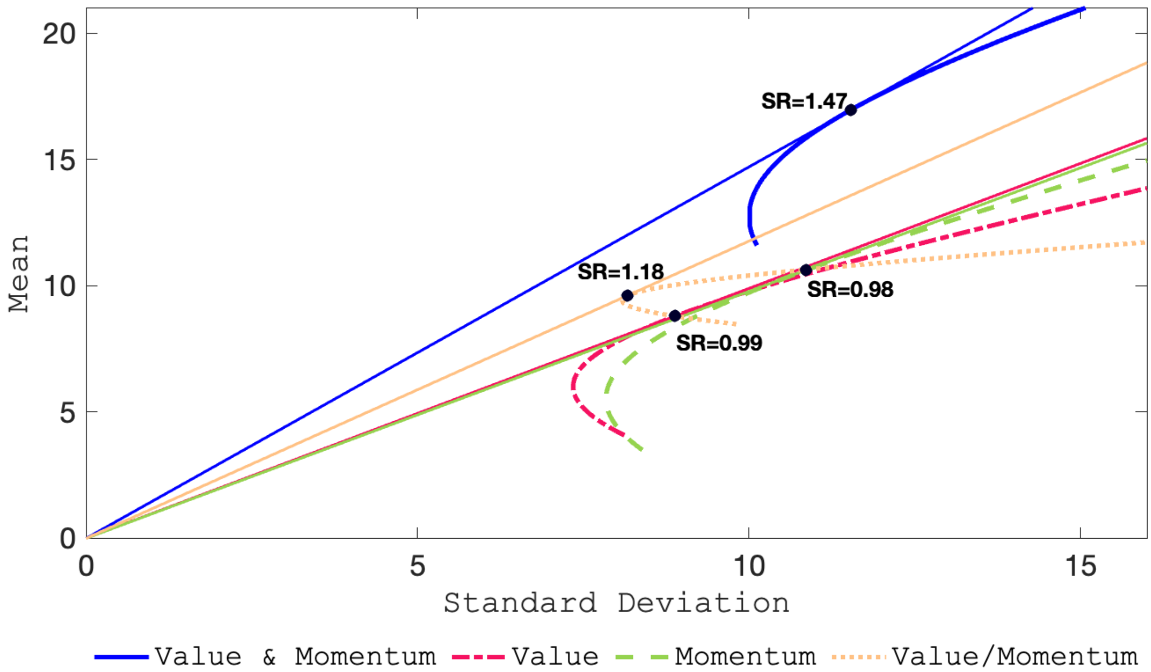


Figure 7. Value and Momentum Efficient Frontiers. The figure presents four efficient frontiers associated with the four tangency portfolios (R_{VM}, R_V, R_M, and $R_{V/M}$). To compute the first three frontiers, we use the latent factors employed in the construction of the respective tangency portfolios. Thus, the frontiers *Value & Momentum*, *Value*, and *Momentum* use the nine latent factors extracted from the joint cross-section of 48 value and momentum, 24 value, and 24 momentum portfolios, respectively. The *Value/Momentum* frontier is constructed by using the R_V and R_M tangency portfolios. We project the tangency lines from the origin to highlight the maximum Sharpe ratio (SR), which is annotated for each tangency portfolio; these correspond to the Sharpe ratios reported in Tables 1 and 5. We scale all frontiers such that the global minimum variance portfolio of the *Value & Momentum* frontier is normalized to have 10% annualized volatility, for comparability. The sample is monthly and covers the 07/1983–12/2023 period.

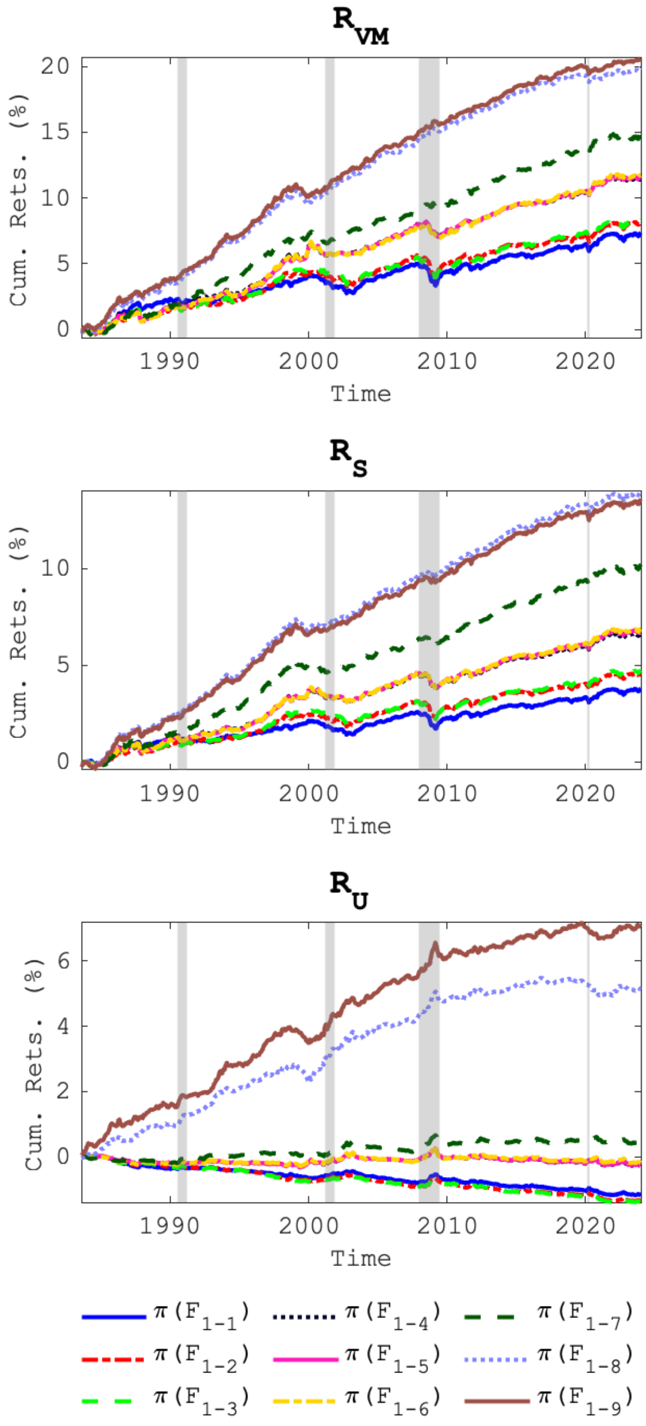


Figure 8. Returns of the Tangency Portfolio and its De-Noised Components. The figure presents cumulative returns of the nine-latent factor tangency portfolio (R_{VM}, top panel), and its de-noised spanned (R_S, middle panel) and unspanned (R_U, bottom panel) components. See Table 5 for details on how the components are obtained. We then de-noise R_S and R_U using the three-pass procedure of Giglio and Xiu (2021), such that $\widehat{F}_{1:9,t} \cdot \widehat{\eta}^T$, with the nine latent factors estimated by applying RP-PCA with baseline RP-weight ($\omega = 20$) to the 48 value and momentum portfolios (see Table 1). The risk exposures and risk premium estimates of R_S and R_U are those presented in Panel A of Tables 6 and 7, respectively. Shaded gray areas are NBER recession periods. The sample is monthly and covers the 07/1983-12/2023 period.

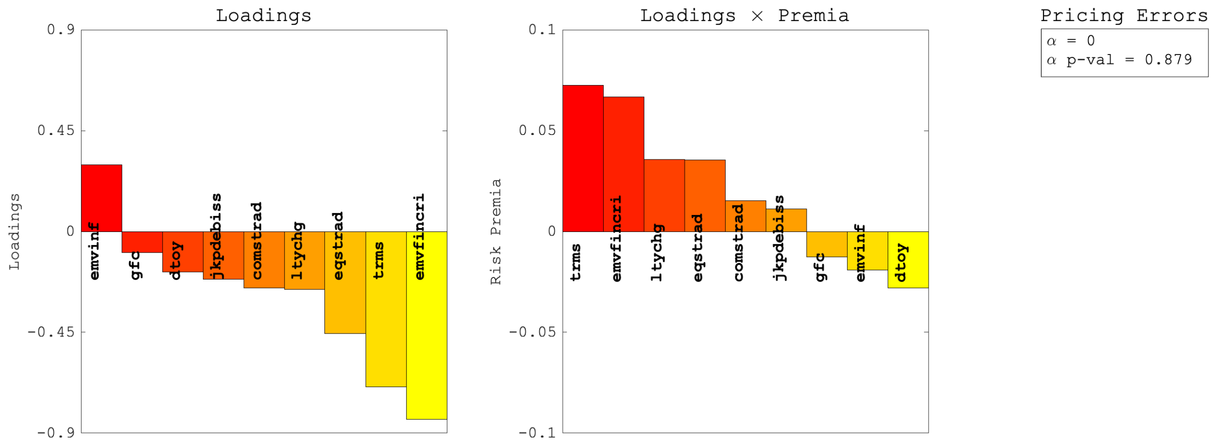


Figure 9. Shrinking the Universe of Priced Macro-Financial Factors. The figure presents the subset of macro-financial risk factors that explain the optimal tangency portfolio. To do this, we regress the nine-latent-factor tangency portfolio returns (R_{VM}) on the priced, 34 macro-financial risk factors (see Table 7) using the LASSO estimator (Tibshirani, 1996). All macro-financial factors are de-noised and return-based. The LASSO penalization parameter selection is based on a 20-fold cross-validation minimization of the mean-squared error loss function (Hansen, 2022). The left panel presents the non-zero loadings of the selected macro-financial factors, while the middle panel interacts the loadings with the factor average returns, or risk premium. The right panel reports the average pricing error (or α), and the associated p-value (p-val), which we obtain by running an OLS spanning regression of R_{VM} onto the selected nine de-noised macro-financial factors, where the standard errors are calculated using Newey and West (1987).

Internet Appendix

[NOT FOR PUBLICATION]

Value and Momentum Leftovers

by

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IA.1 Alternative Asset Pricing Models

Figure IA.1 plots the outputs of cross-sectional asset pricing tests on the 48 value and momentum portfolios for: (i) the AMP three-factor model, (ii) the CAPM, (iii) the Fama-French four-factor model (standard three-factor model with a global market factor plus momentum), and (iv) the Fama-French six-factor model (standard five-factor model with a global market factor plus momentum).

[Figure IA.1 about here.]

Figure IA.2 plots the outputs of cross-sectional asset pricing tests on the 48 value and momentum portfolios for: (i) the Chen-Roll-Ross five-factor model (tested by Cooper et al. (2022)), (ii) our optimal nine-factor model, (iii) the CAPM, and (iv) the AMP three-factor model. Results are presented over the period 07/1983–12/2018, consistent with that tested by Cooper et al. (2022).

[Figure IA.2 about here.]

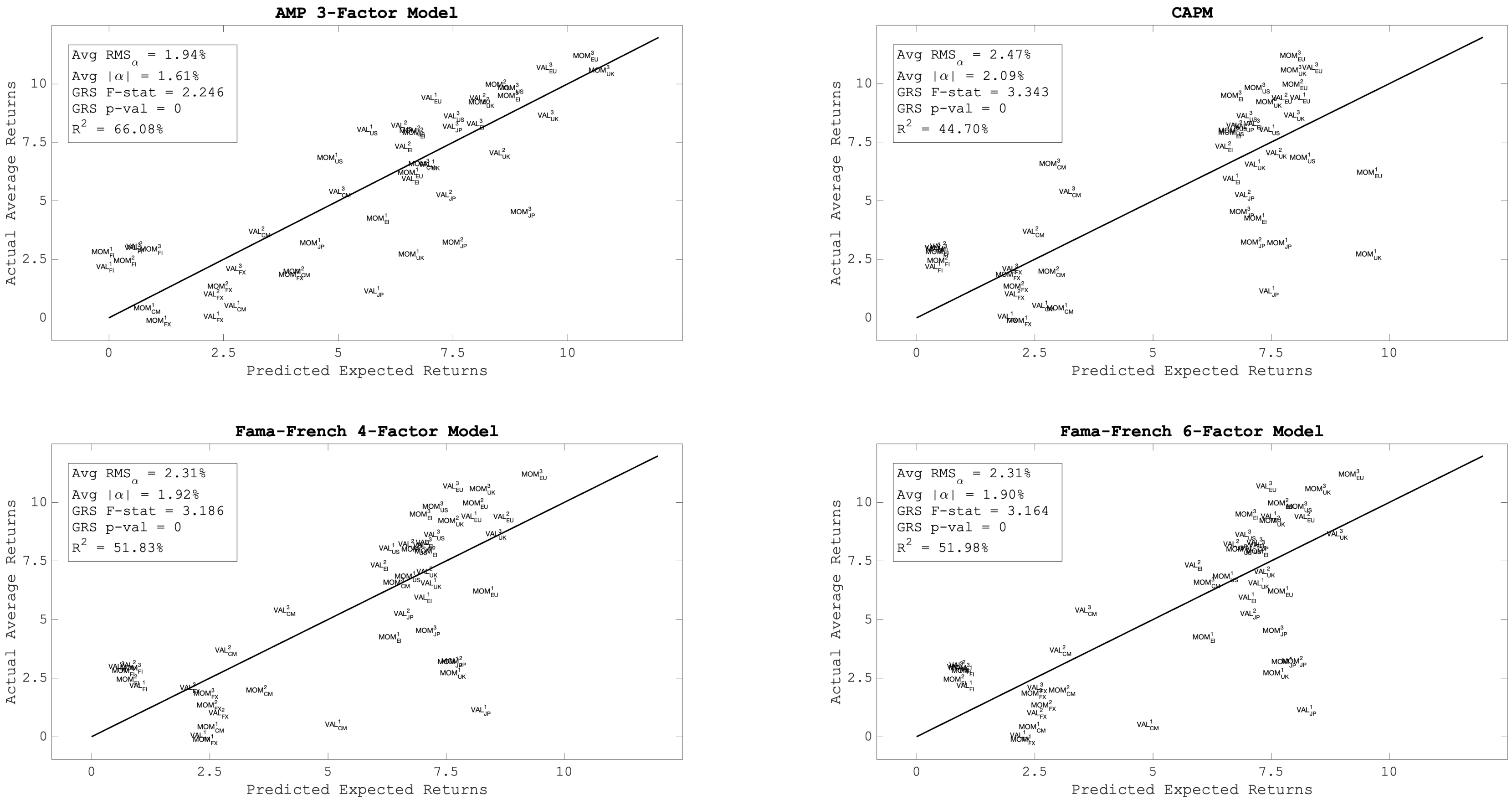

Figure IA.1. Asset Pricing Tests of Alternative Pricing Models (1983–2023). The figure presents Fama and MacBeth (1973) asset pricing tests of four factor models on the 48 value and momentum portfolios of Asness et al. (2013): (i) the three-factor model of AMP (the market, and value and momentum 'everywhere'); (ii) the global CAPM; (iii) the Fama and French (1993) three-factor model, where the US market factor is replaced by the global market factor, plus momentum; and, (iv) the Fama and French (2015) five-factor model, also with the global market and momentum factors, respectively. A 45° line is plotted through the origin, to highlight model fit. Each panel also reports: the average root-mean-square pricing error ($Avg\ RMS_\alpha$), the average absolute alpha ($Avg\ |\alpha|$), the F-statistic and p-value from the Gibbons et al. (1989) test, and the cross-sectional explained variation (R^2), in percent. The sample is monthly, from 07/1983–12/2023.

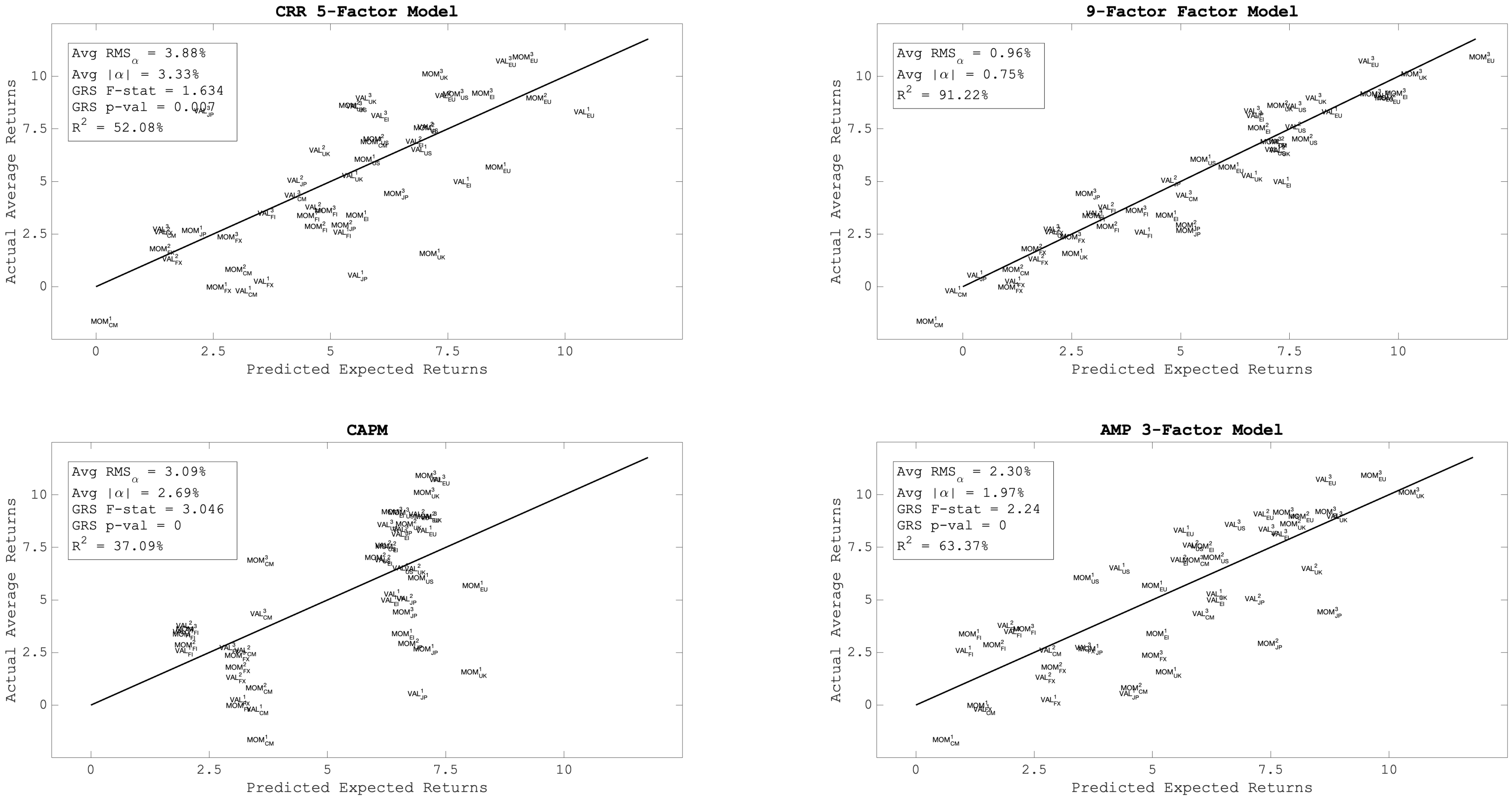

Figure IA.2. Asset Pricing Tests of Alternative Pricing Models (1983-2018). The figure presents Fama and MacBeth (1973) asset pricing tests of four factor models on the 48 value and momentum portfolios of Asness et al. (2013): (i) the five-factor (non-tradable) macroeconomic model of Chen et al. (1986), as employed by Cooper et al. (2022), including industrial production, unexpected inflation, change in expected inflation, term spread, and default spread; (ii) the optimal nine-latent-factor model, presented in the main analysis (see Table 1); (iii) the global CAPM; and, (iv) the three-factor model of AMP (the market, and value and momentum 'everywhere'). A 45° line is plotted through the origin, to highlight model fit. Each panel also reports: the average root-mean-square pricing error ($Avg\ RMS_\alpha$), the average absolute alpha ($Avg\ |\alpha|$), and the cross-sectional explained variation (R^2), in percent. For the CRR, CAPM and AMP models, we also report the F-statistic and p-value from the Gibbons et al. (1989) test. The sample is monthly from 07/1983–12/2018, matching that used in Cooper et al. (2022).

IA.2 The Augmented Three-Pass Procedure

The three-pass method of Giglio and Xiu (2021, GX hereafter) is augmented by initially incorporating the RP-PCA method of Lettau and Pelger (2020a,b, LP hereafter), used to extract the latent factors from the panel of test assets. These approaches are now presented, in turn, alongside the evaluation criteria employed to shed light on the optimal SDF[1].

IA.2.1 Latent Factor Estimation

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

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

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

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

which consists of a systematic 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

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

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

The estimated factor loadings $\widehat{\psi}$ are proportional to the eigenvectors associated with the largest eigenvalues of Σ_{PCA}. The factors $\widehat{F}_t$ are then obtained by regressing the asset returns on the factor loadings. Thus, factors extracted by PCA minimizing 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)[2]. 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

[1] Refer to Lettau and Pelger (2020a,b) and Giglio and Xiu (2021) for more details on the RP-PCA and three-pass methods, respectively.

[2] 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 premia.

PCA regularized by a pricing-error penalty term, which is tantamount to applying PCA to the covariance matrix

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

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., $\widehat{F} = X\widehat{\psi}(\widehat{\psi}^\top\widehat{\psi})^{-1}$. However, the loadings $\widehat{\psi}$ 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

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

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

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

where $\overline{F}$ is the vector of factor expected values. From Equations (IA.4)–(IA.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 $\omega > 0$ helps 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.

IA.2.2 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 by relying on several intuitive metrics, both statistical and economic, guiding the selection of the optimal SDF[3].

The 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, $\widehat{F} \times \widehat{b}_{MV}^{\top}$, where $\widehat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$ is a 1 × K vector; the $\widehat{b}_{MV}$ entries capture the factor weights in the implied SDF, $\varphi_t = 1 - (\widehat{F}_t - \mu_F)\widehat{b}_{MV}^{\top}$.[4] A natural way to identify this optimal SDF would be to perform standard tests of the null hypothesis that all alphas are jointly zero, and select the most parsimonious model which eliminates alpha, on average. However, these types of tests — such as, for example, the Gibbons et al. (1989, GRS hereafter) 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, Kelly and Xiu, 2022, for a detailed review), and hence address some drawbacks of the GRS test, this paper opts for a simple multiple-testing approach. The 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 Equation (IA.1), and as a result the model spans the entire asset space. Hence, it is equivalently informative to perform $N = 48$ 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%, and more stringent (to correct for multiple-hypothesis testing bias) significance levels, as the dimensionality of the SDF varies. In the context of this study, the resultant output seems fairly clear-cut based on this criterion, and the model chosen is the most parsimonious which eliminates all alphas individually, thereby recovering the true SDF of the mean-variance frontier. Robustness, in- and out-of-sample, for model selection based on this criterion is provided in both the main text and Section IA.5.

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

$$X_{nt} = \alpha_n + \widehat{F}_t B_n^{\top} + \epsilon_{nt}, \qquad n = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{IA.7}$$

where the intercept α_n captures the magnitude of the asset-specific pricing errors. Put simply, Equation (IA.7) is the OLS counterpart of the factor model of Equation (IA.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 B_n only when RP-PCA

[3]Statistical tests such as the ones used by LP and GX can be useful in this regard. 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). However, such tests have low power and are prone to underestimating the required number of factors for spanning, as they assume all factors are strong and are unable to detect weaker factors that matter for pricing because of their high Sharpe ratios.

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

uses $\omega = 0$. This is because the pricing-error term of Equation (IA.6) drops out, and hence the two methods minimize the same objective function[5]. Nevertheless, LP argue that the difference turns out to be negligible in the data. Thus, one can use Equation (IA.7) to compute $\overline{RMS}_\alpha = \sqrt{\widehat{\alpha}\widehat{\alpha}^\top/N}$, and $\overline{\sigma}^2_\epsilon = \frac{1}{N}\sum_{n=1}^{N}[Var(\widehat{\epsilon}_n)/Var(X_n)]$ implied by $\widehat{F}$. 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 the trade-off, and pin down the optimal value of the RP-weight, ω. Overall, the RP-PCA method delivers efficient estimates of the latent factors, and the associated statistics help dissect the factors entering the optimal SDF.

IA.2.3 Wild Bootstrap

This section details the application of the wild bootstrap algorithm, originally introduced by Liu (1988) and Mammen (1993), and modified by Giglio et al. (2021) to the case of model estimation via RP-PCA. This is employed to provide p-value estimates for (mean absolute) pricing errors for latent factor models of varying dimensionality.

Step 1. Assume an unconditional factor model with $k = 1, \dots, K$ latent factors, as in Equation (IA.1). Estimate latent factors, $\widehat{F}$, and loadings, $\widehat{\psi}$, via RP-PCA

$$\widehat{F}, \widehat{\psi} = \underset{F,\psi}{\text{argmin}} \left\{ \frac{1}{NT}\sum_{n=1}^{N}\sum_{t=1}^{T}(X_{nt} - F_t\psi_n^\top)^2 + \omega\frac{1}{N}\sum_{n=1}^{N}(\overline{X}_n - \overline{F}\psi_n^\top)^2 \right\}.$$

Given that all test assets are tradable excess returns, the risk premium is given by the mean of the factor. Therefore, pricing errors for the k-factor model may be expressed as

$$\widehat{\alpha}_n^k = \overline{X} - \overline{\widehat{F}}^k\widehat{\psi}_n^{k\top},$$

and mean absolute pricing errors as

$$\overline{|\widehat{\alpha}|}^k = \frac{1}{N}\sum_{n=1}^{N}|\widehat{\alpha}_n^k|.$$

Step 2. For $n = 1, \dots, N$, and $t = 1, \dots, T$, generate a wild bootstrap sample of excess returns, X_{nt}^b, by re-sampling weighted residuals under the null that the full K-factor model achieves full-spanning

$$X_{nt}^b = \widehat{\psi}_n^{K\top}\overline{\widehat{F}}^K + \widehat{\psi}_n^{K\top}(\widehat{F}^K - \overline{\widehat{F}}^K) + \widehat{\epsilon}_{nt}^*, \qquad \widehat{\epsilon}_{nt}^* = \widehat{\epsilon}_{nt}w_{nt},$$

where $\{w_{nt}\}$ is a sequence of i.i.d. random variables, such that $\mathbb{E}(w_{nt}) = 0$ and $\text{Var}(w_{nt}) = 1$. As per Mammen (1993), $w_{nt} = \frac{1}{\sqrt{2}}\eta_{nt} + \frac{1}{2}(\theta_{nt}^2 - 1)$, where η_{nt} and θ_{nt} are independent standard normal.

[5] RP-PCA with $\omega = -1$ yields the same estimates of Equation (IA.7) applied to de-meaned X_{nt} and $\widehat{F}_t$. LP show that, also for $\omega > 0$, RP-PCA loadings can be retrieved using OLS regressions.

Step 3. Given X_{nt}^b, retrieve bootstrap loadings, $\widehat{\psi}^b$, and bootstrap risk premia, $\overline{\widehat{F}}^b$, estimates[6]

$$
\begin{aligned}
\widehat{\psi}_n^b &= (\tilde{F}\mathbb{M}\tilde{F}^\top)^{-1}(\tilde{F}\mathbb{M}\tilde{X}_n^b) \\
\overline{\widehat{F}}^b &= (\widehat{\psi}^b\widehat{\psi}^{b,\top})^{-1}(\widehat{\psi}^b\overline{X}_{nt}^b),
\end{aligned}
$$

where $\tilde{X}_n^b$ and $\tilde{F}$ correspond to the transformed data as described in Equation (IA.8) for $\omega > 0$, and $\mathbb{M} = I_T - T^{-1}\iota_T\iota_T$ is the residual maker matrix.

Step 4. For $k = 1, \ldots, K$, estimate the bootstrap pricing errors

$$
\widehat{\alpha}_n^{b,k} = \overline{X}_n^b - \overline{\widehat{F}}^{b,k}\widehat{\psi}_n^{b,k\top},
$$

and the average absolute bootstrap pricing errors

$$
\overline{|\widehat{\alpha}|}^{b,k} = \frac{1}{N}\sum_{n=1}^{N}|\widehat{\alpha}_n^{b,k}|.
$$

Step 5. Repeat steps 2 to 4 for $b = 1, \ldots, B$ repetitions. After B repetitions, for the hypothesis tests of the null $\mathbb{H}_0$: $\alpha_n^{b,k} = 0$ against the alternatives $\mathbb{H}_A$: $\alpha_n^{b,k} \neq 0$, compute bootstrap two-sided p-values for individual pricing errors for $k = 1, \ldots, K$, as[7]

$$
\widehat{p}_n^k = \frac{1}{B}\sum_{b=1}^{B}\mathbb{1}\{|\widehat{\alpha}_n^{b,k} - \widehat{\alpha}_n^k| > |\widehat{\alpha}_n^k|\}, \qquad n = 1, \ldots, N.
$$

Likewise, for the hypothesis test of the null $\mathbb{H}_0$: $\overline{|\widehat{\alpha}|}^{b,k} = 0$ against the alternative $\mathbb{H}_A$: $\overline{|\widehat{\alpha}|}^{b,k} \neq 0$, compute bootstrap two-sided p-values for mean absolute pricing errors for $k = 1, \ldots, K$, as

$$
\widehat{p}^k = \frac{1}{B}\sum_{b=1}^{B}\mathbb{1}\{(\overline{|\widehat{\alpha}|}^{b,k} - \overline{|\widehat{\alpha}|}^k) > \overline{|\widehat{\alpha}|}^k\}.
$$

Step 6. The p-values for the *individual* pricing errors, $\widehat{p}_n^{b,k}$, must be corrected for multiple-hypothesis testing bias. In line with a vast literature on false discovery control, the Benjamini and Hochberg (1995) procedure is employed. Firstly, p-values for the k-factor model individual test statistics are sorted in ascending order, $\{p_{(1)}^{b,k} \leq \cdots \leq p_{(N)}^{b,k}\}$. For $n = 1, \ldots, N$, reject $\mathbb{H}_0^n$ if $p_n^{b,k} \leq p_{(\widehat{q})}^{b,k}$, where $\widehat{q} = \max\{n \leq N : p_{(n)}^{b,k} \leq \tau n/N\}$, and τ is the given significance level (e.g., 5%)[8].

Note, Hall and Wilson (1991) argue that bootstrap re-sampling should reflect the null hy-

[6] Giglio et al. (2021, Algorithm 3) estimate bootstrap loadings from the bootstrap excess returns using the original input factors, and subsequently estimate bootstrap risk premia. To apply this procedure in the context of estimation using RP-PCA, the estimators require a correction given $\omega > 0$, as detailed in Section IA.2.4, Equation (IA.8).

[7] See Hansen (2022, pp.287) for details of hypothesis testing for bootstrap estimation, and particularly on the importance of centering bootstrapped estimators with sample estimates.

[8] See Giglio et al. (2021) for further details on the application of this approach to the multiple-hypothesis testing of alphas in the wild bootstrap procedure, including alpha screening for inequality hypotheses, and measures of false discovery rate.

pothesis being tested, in order to preserve the power of the test. However, Giglio et al. (2021, pp.3477) "*prove that it is sufficient to impose the joint null hypothesis that all alphas are zero for re-sampling, instead of generating separate bootstrap samples imposing each null hypothesis separately, greatly simplifying the bootstrap procedure.*" Therefore, the results presented generate all bootstrapped excess returns under the null that all individual alphas under the K-factor model (α_n^K) are zero. This, however, relies on full spanning. As pricing error outputs are presented for a range of models with varying degrees of ω penalization in RP-PCA extraction, it is not always the case that the same dimension of factor model will sufficiently span the sample excess returns, to replicate the moment conditions across bootstrap repetitions. In particular, as $\omega <= 0$ does not concentrate the RP-PCA estimator on the first moment, thereby not fitting the model to minimize pricing errors, larger dimensions of factor models are required to span test asset returns. As such, for $\omega <= 0$, $K = 20$, whereas for $\omega > 0$, $K = 10$ is sufficient. All results are robust to variations around these dimensions.

IA.2.4 Three-Pass Procedure

Given identification of the optimal latent tangency portfolio, the GX three-pass method produces three key characteristics: the exposures of test assets to the latent factors; the latent factor market prices of risk; and, spanning of the true SDF for the full cross-section of test assets, providing loadings, explained variation and accurate estimates of candidate factors' risk premia. The implementation of this approach is now presented.

1. `Test-Asset Exposures to Latent Factors` (ψ). The first pass consists of estimating test asset risk exposures to latent factors. As 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 outlined, 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 Equation (IA.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

$$\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}, \qquad n = 1, \dots, N, \quad t = 1, \dots, T, \tag{IA.8}$$

where $\tilde{X}_{nt} = X_{nt} + \tilde{\omega}\bar{X}_{nt}$, and the vector $\tilde{F}_t$ contains elements defined as $\tilde{F}_{kt} = \widehat{F}_{kt} + \tilde{\omega}\bar{F}_{kt}$ for $k = 1, \dots, K$, 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 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,

$$\overline{X}_n = \widehat{\psi}_n \gamma^\top + a_n, \quad n = 1, \dots, N, \tag{IA.9}$$

where γ is the $1 \times K$ vector of the latent factor prices of risk.[9]

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

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

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

$$\widehat{\lambda}_g = \widehat{\gamma}\widehat{\eta}^\top, \tag{IA.11a}$$

$$\widehat{g}_t = \widehat{F}_t\widehat{\eta}^\top, \tag{IA.11b}$$

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

`Rotation Invariance of Risk Premia`. Under the GX procedure, 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, $\widehat{\widehat{F}}_t \equiv \widehat{F}_t H^{-1}$, for any full-rank $k \times k$ matrix H, instead of the original factors $\widehat{F}_t$. 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 $\widehat{\widehat{\gamma}} \equiv \widehat{\gamma}H^{-1}$ and $\widehat{\widehat{\eta}} \equiv \widehat{\eta}H^\top$, it holds that

$$\widehat{\lambda}_g = \widehat{\gamma}\widehat{\eta}^\top = \widehat{\gamma}H^{-1}H\widehat{\eta}^\top = \widehat{\widehat{\gamma}}\widehat{\widehat{\eta}}^\top. \tag{IA.12}$$

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

[9] 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 determines the uncertainty around the estimates, accounted for in the computation of the asymptotic standard errors of the candidate factors' prices of risk, allowing for evaluation the fit of the latent-factor model.

IA.3 Value and Momentum Test Assets and Factors

Table IA.1 presents summary statistics of the updated cross-section of 48 value and momentum portfolio excess returns, as well as high-minus-low and rank factors, constructed by AMP.

[Table IA.1 about here.]

Table IA.2 presents correlations between the *stock* and *non-stock* value and momentum rank factors of AMP for the updated cross-section of 48 value and momentum test asset excess returns.

[Table IA.2 about here.]

IA.4 Candidate Risk Factors

Table IA.3 provides names, descriptions and sample periods of the universe of the macro-financial candidate factors employed in the third-pass of the Giglio and Xiu (2021) procedure.

[Table IA.3 about here.]

IA.5 Additional Results and Simulation Analysis

IA.5.1 Latent Factor Diagnostics

Figure IA.3 presents the cumulative returns of each of the nine latent factors comprising the optimal pricing kernel.

[Figure IA.3 about here.]

Table IA.4 presents diagnostics of the latent factors extracted from the full cross-section of 48 value and momentum test assets, using RP-PCA with a range of RP-weights, including $\omega = \{-1, 0, 5, 10, 20, 50\}$.

[Table IA.4 about here.]

Figure IA.4 presents, for the optimal nine-factor model tangency portfolio, the weight attributable to each of the test assets (left panel), and the same measure in units of risk premia given the unconditional test asset excess returns (right panel).

[Figure IA.4 about here.]

Table IA.1
Performance of Value and Momentum Portfolios Across Markets and Asset Classes

The table presents the summary statistics of the updated 48 value and momentum portfolio test asset returns and corresponding factors of Asness et al. (2013). Reported are the average excess returns (*Mean*), *t*-statistics (*t-stat*), standard deviations (*Stdev*), and Sharpe ratios (*SR*), for value, momentum and equally-weighted combination strategies in each of the following markets: US stocks, UK stocks, Continental Europe stocks, Japan stocks, equity index futures, currencies, government bonds, and commodities. The panel is balanced, with a monthly sample from 07/1983–12/2023. Securities are sorted according to their prescribed strategy signal and split into terciles to form three — low, middle, and high — portfolios, P1, P2, and P3, respectively. Panel A presents stock strategies, all of which are value-weighted by their beginning-of-month capitalizations. Panel B contains non-stock strategies, which are equal-weighted. Each strategy also reports a high-minus-low return (*P3-P1*), as well as the corresponding rank-weighted factor return (*Factor*), which weights each asset in proportion to its cross-sectional rank based on either value or momentum. The '*50/50*' strategies are averages of the related spread strategies. Results are also reported for averages of the individual strategies across all stock markets ('Global stocks'), all other asset markets ('Global others'), and across all asset classes and markets combined ('Global all'). For the global returns, average return series are weighted by the inverse of the standard deviation of a passive benchmark for each corresponding market, rescaled to sum to one. For stocks, the corresponding net MSCI index return is used, whereas the other asset classes simply use an equally-weighted average of the securities in that asset class, following the initial procedure AMP.

Panel A: Individual Stock Portfolios

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3-P1	Factor	P1	P2	P3	P3-P1	Factor	P3-P1	Factor
US stocks	Mean	8.04	8.20	8.62	0.58	2.17	6.83	8.00	9.81	2.98	4.80	1.78	3.49
	t-stat	2.96	3.55	3.50	0.30	0.91	2.34	3.52	3.68	1.26	1.90	1.72	3.25
	Stdev	17.31	14.69	15.65	12.39	15.25	18.62	14.47	16.97	15.03	16.11	6.57	6.82
	SR	0.46	0.56	0.55	0.05	0.14	0.37	0.55	0.58	0.20	0.30	0.27	0.51
										Correlation (Val,Mom) =		−0.56	−0.62
UK stocks	Mean	6.54	7.03	8.64	2.09	3.37	2.71	9.20	10.57	7.86	8.45	4.98	5.91
	t-stat	2.36	2.46	2.82	0.95	1.48	0.76	3.40	3.48	3.08	3.41	3.97	5.49
	Stdev	17.67	18.19	19.50	13.96	14.47	22.59	17.20	19.33	16.26	15.78	7.97	6.84
	SR	0.37	0.39	0.44	0.15	0.23	0.12	0.53	0.55	0.48	0.54	0.62	0.86
										Correlation (Val,Mom) =		−0.45	−0.59
Europe stocks	Mean	9.40	9.39	10.68	1.28	2.09	6.20	9.96	11.19	4.99	6.48	3.14	4.28
	t-stat	3.22	3.43	3.57	0.71	1.24	1.81	3.61	3.86	2.22	3.11	3.07	4.68
	Stdev	18.56	17.41	19.04	11.56	10.76	21.77	17.56	18.47	14.30	13.23	6.51	5.83
	SR	0.51	0.54	0.56	0.11	0.19	0.28	0.57	0.61	0.35	0.49	0.48	0.73
										Correlation (Val,Mom) =		−0.51	−0.54

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Table IA.1 — Continued

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3-P1	Factor	P1	P2	P3	P3-P1	Factor	P3-P1	Factor
Panel A: Individual Stock Portfolios													
Japan stocks	Mean	1.13	5.25	8.16	7.03	7.93	3.18	3.21	4.52	1.34	1.55	4.19	4.74
	t-stat	0.33	1.74	2.54	2.98	3.69	0.88	1.06	1.36	0.47	0.62	3.42	4.63
	Stdev	21.67	19.17	20.41	15.03	13.69	23.08	19.33	21.12	18.23	15.95	7.79	6.51
	SR	0.05	0.27	0.40	0.47	0.58	0.14	0.17	0.21	0.07	0.10	0.54	0.73
										Correlation (Val,Mom) =		−0.58	−0.62
Global stocks	Mean	5.92	8.01	10.20	4.28	3.66	4.83	7.78	9.37	4.54	5.30	4.41	4.48
	t-stat	2.02	2.96	3.49	2.25	2.07	1.44	2.88	3.20	1.95	2.71	4.56	5.64
	Stdev	18.68	17.22	18.58	12.12	11.24	21.31	17.17	18.63	14.84	12.44	6.16	5.06
	SR	0.32	0.47	0.55	0.35	0.33	0.23	0.45	0.50	0.31	0.43	0.72	0.89
										Correlation (Val,Mom) =		−0.60	−0.64
Panel B: Other Asset Class Portfolios													
Country Indices	Mean	5.94	7.32	8.29	2.35	2.19	4.24	7.90	9.49	5.25	4.69	3.80	3.44
	t-stat	2.48	3.02	3.20	1.64	1.53	1.64	3.34	3.83	3.23	2.83	4.68	4.35
	Stdev	15.25	15.40	16.46	9.11	9.08	16.41	15.05	15.75	10.35	10.53	5.17	5.03
	SR	0.39	0.48	0.50	0.26	0.24	0.26	0.53	0.60	0.51	0.45	0.74	0.68
										Correlation (Val,Mom) =		−0.44	−0.48
Currencies	Mean	0.05	1.01	2.09	2.04	2.39	−0.13	1.33	1.83	1.96	1.63	2.00	2.01
	t-stat	0.04	0.77	1.64	1.57	2.02	−0.09	1.04	1.42	1.41	1.27	2.76	3.10
	Stdev	8.22	8.30	8.10	8.27	7.53	8.63	8.08	8.22	8.88	8.17	4.62	4.13
	SR	0.01	0.12	0.26	0.25	0.32	−0.01	0.16	0.22	0.22	0.20	0.43	0.49
										Correlation (Val,Mom) =		−0.42	−0.45
Fixed income	Mean	2.18	3.04	2.98	0.80	0.64	2.81	2.44	2.93	0.12	0.55	0.46	0.59
	t-stat	2.21	3.51	3.54	0.93	0.84	3.18	2.91	3.27	0.16	0.79	0.90	1.31
	Stdev	6.26	5.52	5.35	5.53	4.87	5.62	5.33	5.69	4.69	4.41	3.25	2.88
	SR	0.35	0.55	0.56	0.15	0.13	0.50	0.46	0.51	0.02	0.12	0.14	0.21
										Correlation (Val,Mom) =		−0.20	−0.23

(*continued over page*)

Table IA.1 — Continued

Panel B: Other Asset Class Portfolios

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3-P1	Factor	P1	P2	P3	P3-P1	Factor	P3-P1	Factor
Commodities	Mean	0.51	3.67	5.39	4.88	5.40	0.41	1.97	6.58	6.17	5.31	5.53	5.35
	t-stat	0.19	1.52	2.12	1.57	1.74	0.16	0.95	2.34	2.08	1.77	3.43	3.43
	Stdev	17.48	15.33	16.20	19.77	19.73	16.42	13.28	17.87	18.89	19.05	10.25	9.92
	SR	0.03	0.24	0.33	0.25	0.27	0.02	0.15	0.37	0.33	0.28	0.54	0.54
										Correlation (Val,Mom) =		−0.44	−0.48
Global others	Mean	2.21	3.83	4.67	2.45	2.07	2.17	3.40	4.98	2.81	2.15	2.63	2.11
	t-stat	2.06	3.81	4.31	2.57	2.87	1.96	3.49	4.57	2.77	2.67	5.13	5.56
	Stdev	6.84	6.39	6.89	6.07	4.59	7.04	6.20	6.94	6.46	5.12	3.27	2.41
	SR	0.32	0.60	0.68	0.40	0.45	0.31	0.55	0.72	0.44	0.42	0.81	0.87
										Correlation (Val,Mom) =		−0.46	−0.51
Global all	Mean	4.16	6.46	8.02	3.85	2.72	3.76	5.96	8.05	4.30	3.43	4.07	3.07
	t-stat	2.27	3.70	4.26	3.13	3.00	1.84	3.46	4.31	2.90	3.16	6.09	7.02
	Stdev	11.69	11.11	11.97	7.84	5.75	12.99	10.97	11.89	9.41	6.91	4.26	2.79
	SR	0.36	0.58	0.67	0.49	0.47	0.29	0.54	0.68	0.46	0.50	0.96	1.10
										Correlation (Val,Mom) =		−0.52	−0.63

Table IA.2

Correlation of Value and Momentum Strategies Across Markets and Asset Classes

The table reports the correlations among the updated value and momentum (rank factor) strategies of Asness et al. (2013). Panel A reports correlations of returns using the global stock and other asset classes value and momentum factors, which are computed as the volatility-weighted average of all individual stock (and non-stock) value (and momentum) strategies. The diagonal elements are constructed by first determining the correlation between one individual market (e.g., the US) and the combined volatility-weighted average of the other markets (the UK, Continental Europe and Japan), and then subsequently switching the subsets, culminating in four correlation coefficients, of which an equally-weighted average is then taken to form the statistic. The off-diagonal elements are simple Pearson correlation coefficients between the two strategies. Panel B reports the correlations of the aggregate stock value and momentum strategies with each of the non-stock value and momentum strategies. Correlations are computed using quarterly returns, mitigating the influence of non-synchronous trading across markets. Individual t-statistics for the significance of the correlations of each pair of aggregate returns are reported, where ***, ** and * correspond to a rejection of the null hypothesis of zero at the 1%, 5% and 10% confidence levels, respectively.

Panel A: Correlation of Average Return Series

	Stock Value	Non-stock Value	Stock Momentum	Non-stock Momentum
Stock value	0.69***	0.17**	−0.60***	−0.17**
Non-stock value		0.06	−0.24***	−0.45***
Stock momentum			0.66***	0.46***
Non-stock momentum				0.24**

Panel B: Correlation of Average Stock Series with Each Non-stock Series

	Country Index Value	Currency Value	Fixed Income Value	Commodity Value	Country Index Momentum	Currency Momentum	Fixed Income Momentum	Commodity Momentum
Global Stock value	0.39***	0.15*	−0.08	0.04	−0.17**	−0.13*	−0.10	−0.04
Global Stock momentum	−0.31***	−0.18**	0.05	−0.15*	0.48***	0.34***	0.17**	0.21***

Table IA.3
Candidate Risk Factors

The table reports the names (*Name*) and descriptions (*Description*), including sources, of candidates factors used in the spanning regressions and third-pass of the Giglio and Xiu (2021) procedure in the main text. Factors are sorted into their respective categories, and listed alphabetically. Where multiple factors originate from one source, they are grouped together and placed in the category which most of the variables relate to. Given that all series are not consistently updated to match the time-series of the test assets, the beginning (*Start*) and end (*End*) dates are also reported. In the empirical analysis, tradable factors are raw, whereas non-tradable factors are expressed as innovations taken as residuals from an AR(1) process.

Name	Description	Start	End
	Decomposition		
R_{VM}	The return of the optimal nine-factor tangency portfolio, where factors are extracted from the full cross-section of 48 value and momentum test assets using RP-PCA with RP-weight $\omega = 20$ (see Table 1).	07/1983	12/2023
R_S	The *spanned* component from the decomposition regression, as set out in Table 5, of the optimal nine-factor tangency portfolio return (R_{VM}) on the mean-variance-weighted combination of the two separate nine-factor value (R_V) and nine-factor momentum (R_M) tangency portfolios. It captures the component of the optimal tangency portfolio return owing to the diversification benefits of investing in both value and momentum strategies.	07/1983	12/2023
R_U	The *unspanned* component from the decomposition regression, as set out in Table 5, of the optimal nine-factor tangency portfolio return (R_{VM}) on the mean-variance-weighted combination of the two separate nine-factor value (R_V) and momentum (R_M) tangency portfolios. It captures the component of the optimal tangency portfolio return owing to the use of the full cross-section of 48 test assets, comprising all individual portfolio covariances beyond the combination of the separate 24 value and 24 momentum tangency portfolio returns.	07/1983	12/2023
R_V	The nine-factor tangency portfolio extracted from the cross-section of 24 value test assets using RP-PCA with RP-weight $\omega = 20$.	07/1983	12/2023
R_M	The nine-factor tangency portfolio extracted from the cross-section of 24 momentum test assets using RP-PCA with RP-weight $\omega = 20$.	07/1983	12/2023
	Tradable		
bab	Global betting-against-beta equity risk factor (Frazzini and Pedersen, 2014). Source: AQR Capital Management's website: https://www.aqr.com/Insights/Datasets.	02/1987	12/2023
bdstrad fxstrad comstrad irstrad eqstrad	Trend-following factors for hedge fund returns, including: bond (bdstrad), currency (fxstrad), commodity (comstrad), short-term interest rate (irstad), and equity (eqstrad) trend-following factors formed from look-back straddles (Fung and Hsieh, 2001). Source: David Hsieh's website: http://people.duke.edu/ dah7/DataLibrary/TF-Fac.xls.	01/1994	12/2023
eqcar ficar fxcar comcar	Carry factors for a range of asset classes, including: equity carry (eqcar), bond carry (ficar), currency carry (fxcar), and commodity carry (comcar) (Koijen et al., 2018). Source: Ralph Kojien's website.	02/1980	07/2021
jkpacc jkpdebiss jkpinv jkplolev jkplorsk jkpmom jkpprofg jkpprof jkpqual jkpseas jkpstrmv jkpsize jkpval	13 developed-market theme factors, which consolidate information from 153 characteristics, including: accruals (acc), debt issuance (debiss), investment (inv), low leverage (lolev), low risk (lorsk), momentum (mom), profit growth (profg), profitability (prof), quality (qual), seasonality (seas), short-term reversal (strmv), size (size), and value (val) (Jensen et al., 2023). Source: Jensen, Kelly and Pedersen's Global Factor Data website: https://jkpfactors.com.	01/1986	12/2023
vrp	Variance risk premium estimate (difference between model-free implied and realized volatilities) (Bollerslev et al., 2009). Source: Hao Zhou's website.	01/1990	12/2022

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Table IA.3 — Continued

Name	Description	Start	End
	Non-tradable		
adbear	Arrow-Debreu bear-spread security from S&P 500 index options (Lu and Murray, 2019). Source: Zhongjin Lu's website.	01/1996	08/2015
avgcor	Average correlations amongst the 500 largest stocks (Pollet and Wilson, 2010). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
corp	Spread between BAA and AAA-rated bond yields. Source: https://fred.stlouisfed.org/.	01/1986	12/2023
disag	Dispersion of earnings-per-share long-term growth rate forecasts by analysts from the I/B/E/S database, value-weighted across stocks, as a measure of analyst forecast disagreement (Yu, 2011). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
dtoy dtoat	Scaled difference to the 52-week high of the Dow Jones index, and the difference to the lifetime high, as proxies for the degree to which traders under- and overreact to news (Li and Yu, 2012). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
emv emvpol emvout emvinf emvir emvfx emvmon emvfisc emvtrad emvfincri	Newspaper-based equity market volatility trackers that move with the CBOE Volatility Index (VIX) and S&P 500 realized volatility of returns. Alongside the overall tracker (emv), more granular trackers, used to construct the overall measure, are considered, including: a general Policy-related (emvpol); Macroeconomic News and Outlook (emvout); Macro - Inflation (emvinf); Macro- Interest Rates (emvir); Macro - Exchange Rates (emvfx); Monetary Policy (emvmon); Fiscal Policy (emvfisc); Trade Policy (emvtrad); and, Financial Crises (emvfincri) (Baker et al., 2016). Source: https://www.policyuncertainty.com.	01/1985	12/2023
epu gepu gepuppp	Indices of US economic policy uncertainty (epu), global economic policy uncertainty (gepu), and gepu corrected for purchasing power parity (gepuppp), computed from newspaper coverage frequency (Baker et al., 2016). Source: https://www.policyuncertainty.com.	01/1985	12/2023
finunc macunc realunc	Financial (finunc), macroeconomic (macunc), and real (realunc) uncertainty indices (Jurado et al., 2015; Ludvigson et al., 2021). Source: Sydney Ludvigson's website.	07/1983	12/2023
gpr gpr(thrts) gpr(acts)	Geopolitical risk index (overall, threats, and acts) (Caldara and Iacoviello, 2022). Source: Matteo Iacoviello website.	01/1985	12/2023
fsi	US Newspaper-based Financial Stress Indicator. Source: https://www.policyuncertainty.com.	11/1983	12/2023
geqrv	Global equity volatility factor (Lustig et al., 2011). Source: Adrien Verdelhan's website.	11/1983	05/2021
gfc	Global financial cycle factor extracted from a dynamic factor model for a large and heterogeneous panel of risky asset prices traded around the world (Miranda-Agrippino and Rey, 2020). Source: Silvia Miranda-Agrippino's website.	07/1983	04/2019
icap	Intermediary capital risk factor based on the equity capital ratio of financial intermediaries (He et al., 2017). Source: Zhiguo He's website.	07/1983	12/2023
ltychg	Change in US long-term (10-year) yield. Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
impvar	Implied variance from equity index options (Bakshi et al., 2011). Source: Amit Goyal's website (data for Goyal et al., 2024).	01/1996	02/2023
mf1 mf2 mf3	First three principal components extracted from a large dataset of macro and financial time series (Ludvigson and Ng, 2009). Source: Sidney Ludvigson's website	07/1983	12/2023
move	Merrill Lynch Option Volatility Estimate Index. Source: Datastream.	04/1988	12/2023

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Table IA.3 — Continued

Name	Description	Start	End
mp ui dei uts upr	5-factor macroeconomic risk model of Chen et al. (1986), including: industrial production (mp), unexpected inflation (ui), change in expected inflation (dei), term spread (uts), and default spread (upr) (Chen et al., 1986). Source: Provided by Richard Priestley (data for Cooper et al., 2022).	01/1983	12/2023
mpmar mpmarinf	Conventional monetary policy (mpmar) and information (mpmarinf) instruments of Miranda-Agrippino and Ricco (2021) and Degasperi and Ricco (2021). Source: Riccardo Degasperi's website.	01/1991	12/2018
mpjkff4 mpjksporg mpjkpc mpjkspnew mpjkpm mpjkcbi mpjkmed mpjkcbimed	US monetary policy instruments from Jarociński and Karadi (2020), including: original surprises in the three-month-ahead Fed Funds futures (mpjkff4); original surprises in the S&P500 (mpjksporg); surprise in the "policy indicator", taken to be the first principal component of the surprises in interest rate derivatives with maturities from 1 month to 1 year (which includes MP1, FF4, ED2, ED3, ED4) (mpjkpc); surprises in the S&P500 (mpjkspnew); conventional "poor man" monetary policy (mpjkpm) and information (mpjkcbi) instruments; and, monetary policy (mpjkmed) and information (mpjkcbimed) shocks based on median rotation of sign restrictions. Source: Marek Jarocinski's website.	02/1990	12/2016
mpbs mpbsort mpbsortfit	Monetary policy surprise non-orthogonalised (mpbs), orthogonalised (mpbsort), and information (mpbsortfit) instruments, of Bauer and Swanson (2023). The conventional policy instrument is constructed as the first principal component of the change in the spread between the current-quarter Eurodollar futures and the three-quarter-ahead Eurodollar futures contracts. Orthogonalisaton is with respect to alternative macroeconomic data release surprises (nonfarm payrolls, unemployment, GDP, and inflation) as well as changes the S&P500, yield curve slope, and commodity prices. Source: Michael Bauer's website: https://www.michaeldbauer.com/research.	02/1988	12/2019
mjratesu1 mjodysu2 mjdelphu3 mjlsapu4 mjsummp	US monetary policy instruments of Jarociński (2024), including: conventional monetary poicy shock (mjratesu1); forward guidance monetary policy shock (mjodysu2); information shock (mjdelphu3); quantitative easing shock (mjlsapu4); and sum of all monetary policy shocks (mjsummp). All are non-Gaussian. Source: Marek Jarocinski's website.	01/1991	12/2023
noise	Market-wide liquidity measure based on the connection between the amount of arbitrage capital in the market and observed price deviations (noise) in U.S. Treasury bonds (Hu et al., 2013). Source: Jun Pan's website.	01/1987	12/2023
ogap	US output gap (Cooper and Priestley, 2009). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
perunc	Perceived uncertainty, measured as the price of volatile stocks, defined as the book-to-market ratio of low-volatility stocks minus book-to-market ratio of high-volatility stocks (Pflueger et al., 2020). Source: Carolin Pflueger's website.	07/1983	12/2023
psliq	Pastor and Stambaugh equity liquidity factor (Pástor and Stambaugh, 2003). Source: Lubos Pastor's website.	07/1983	12/2023
sent	Sentiment Index (Baker and Wurgler, 2007). Source: Jeffrey Wurgler's website.	07/1983	12/2023
shtint	Aggregate short interest in the market, calculated as the log of the equal-weighted mean of short interest across publicly listed US stocks (Rapach et al., 2016). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
skew	Average cross-sectional skewness across firms (Jondeau et al., 2019). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
tail	Tail risk estimated from the cross-section of stock returns (Kelly and Jiang, 2014). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023
ted	TED spread. Source: https://fred.stlouisfed.org/.	01/1986	12/2021
trms	US Term spread (difference between 10-year Treasury bill yield and T-bill). Source: Amit Goyal's website (data for Welch and Goyal, 2008).	07/1983	12/2023
vix/vxo	CBOE S&P 100 Volatility Index. Source: https://fred.stlouisfed.org/.	01/1986	12/2023
ygap	Stock-bond yield gap (so-called "Fed model"), calculated as the dividend-price ratio net of the 10-year Treasury bond yield (Maio, 2013). Source: Amit Goyal's website (data for Goyal et al., 2024).	07/1983	12/2023

Table IA.4
Latent Factor Pricing Diagnostics (Full)

The table presents model diagnostics of the first two steps of the three-pass asset pricing procedure of Giglio and Xiu (2021). Specifically, we examine the properties of the latent factors and associated tangency portfolios (Panel A), and the performance of the latent-factor models (Panel B). We do so by examining the first ten latent factors, i.e., F_k for $k = 1, 2, \ldots, 10$, and models including an increasing number of latent factors. We estimate the latent factors applying the RP-PCA method of Lettau and Pelger (2020a,b) with a range of RP-weights, including $\omega = \{-1,\ 0,\ 5,\ 10,\ 20,\ 50\}$, to the 48 value and momentum test asset returns. Specifically, Panel A1 shows the annualized average return of each latent factor (μ_{F_k}), where ***, ** and * indicate statistical significance at the 1%, 5% and 10% confidence levels, respectively, based on Newey and West (1987) standard errors; the k-th factor's Sharpe ratio (SR); and, the k-th factor's weight in the tangency portfolio ($\widehat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$). Panel A2 presents the annualized maximum Sharpe ratio of the tangency portfolios (SR), and the change in the Sharpe ratio owing to the inclusion of the next additional latent factor, k (ΔSR). Panel B provides several statistics and evaluation criteria for the first-pass (Equation (7): $\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}$) and second-pass (Equation (8): $\overline{X}_n = \widehat{\psi}_n \gamma^\top + a_n$) regressions, where X are the test asset returns, ψ are the asset risk exposures, and γ are the latent factor prices of risk (which, by no arbitrage equal the factor average returns). Panel B1 reports the average idiosyncratic variance ($\overline{\sigma}^2_\epsilon = 1/N \sum_{n=1}^{N} [Var(\widehat{\epsilon}_n)/Var(X_n)]$), and the average root-mean-square alpha (pricing error) from the time-series regressions ($\overline{\text{RMS}}_\alpha = \sqrt{\widehat{\alpha}\widehat{\alpha}'/N}$). Panel B2 shows the mean absolute pricing error from the cross-sectional regression (MAE), and the percentage of variation explained by the tangency portfolio (R^2). Panel B3 presents the number of individually statistically significant alphas for each factor model. The statistical significance of individual alphas and mean absolute pricing errors are estimated using a wild bootstrap procedure similar to that of Giglio et al. (2021), where multiple-hypothesis testing biases are addressed via the Benjamini and Hochberg (1995, BH) false discovery control approach. Thus, $\alpha^{BH}_{\xi\%}$ represents the number of individually significant pricing errors at the BH-corrected $\xi = \{10\%, 5\%, 1\%\}$ levels, respectively. See Section IA.2.3, in the Internet Appendix, for details of the wild bootstrap algorithm. The sample spans the 07/1983–12/2023 period, return data are at monthly frequency.

	Panel A: Factors & Tangency Portfolios						Panel B: Two-Pass Statistics							
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
$\omega = -1$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	40.52***	0.49	0.05	$\pi(F_{1-1})$	0.49	0.49	F_{1-1}	44.91	2.52	2.14***	46.39	35	33	29
F_2	7.61	0.21	0.05	$\pi(F_{1-2})$	0.54	0.04	F_{1-2}	33.87	2.27	1.86***	57.78	30	30	22
F_3	2.36	0.08	0.02	$\pi(F_{1-3})$	0.54	0.01	F_{1-3}	26.31	2.24	1.81***	61.81	29	26	20
F_4	0.88	0.04	0.01	$\pi(F_{1-4})$	0.54	0.00	F_{1-4}	22.16	2.24	1.80***	61.83	31	28	20
F_5	6.38*	0.30	0.12	$\pi(F_{1-5})$	0.62	0.08	F_{1-5}	18.47	2.04	1.65***	67.65	28	24	22
F_6	0.87	0.05	0.02	$\pi(F_{1-6})$	0.62	0.00	F_{1-6}	15.59	2.04	1.65***	67.66	29	25	21
F_7	0.87	0.05	0.03	$\pi(F_{1-7})$	0.62	0.00	F_{1-7}	13.26	2.04	1.65***	67.76	27	26	23
F_8	1.26	0.08	0.05	$\pi(F_{1-8})$	0.63	0.01	F_{1-8}	11.35	2.03	1.64***	67.83	27	27	22
F_9	0.68	0.05	0.04	$\pi(F_{1-9})$	0.63	0.00	F_{1-9}	10.12	2.02	1.65***	69.63	28	27	22
F_{10}	4.87***	0.42	0.31	$\pi(F_{1-10})$	0.76	0.13	F_{1-10}	9.04	1.90	1.55***	69.85	24	22	17

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Table IA.4 — Continued

	Panel A: Factors & Tangency Portfolios						Panel B: Two-Pass Statistics							
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
$\omega = 0$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	40.68***	0.50	0.05	$\pi(F_{1-1})$	0.50	0.50	F_{1-1}	44.91	2.52	2.09***	48.24	35	33	30
F_2	7.72	0.21	0.05	$\pi(F_{1-2})$	0.54	0.04	F_{1-2}	33.87	2.27	1.81***	59.52	31	29	22
F_3	2.40	0.08	0.02	$\pi(F_{1-3})$	0.54	0.01	F_{1-3}	26.31	2.24	1.75***	63.32	31	27	20
F_4	0.97	0.04	0.02	$\pi(F_{1-4})$	0.55	0.00	F_{1-4}	22.16	2.24	1.75***	63.36	31	28	19
F_5	6.67*	0.31	0.12	$\pi(F_{1-5})$	0.63	0.08	F_{1-5}	18.47	2.04	1.59***	69.50	28	24	21
F_6	0.91	0.05	0.02	$\pi(F_{1-6})$	0.63	0.00	F_{1-6}	15.59	2.03	1.59***	69.52	28	26	21
F_7	0.95	0.06	0.03	$\pi(F_{1-7})$	0.63	0.00	F_{1-7}	13.26	2.03	1.59***	69.58	28	27	24
F_8	1.43	0.09	0.05	$\pi(F_{1-8})$	0.64	0.01	F_{1-8}	11.36	2.02	1.57***	69.69	27	26	22
F_9	1.20	0.10	0.07	$\pi(F_{1-9})$	0.65	0.01	F_{1-9}	10.12	2.01	1.59***	71.75	28	27	22
F_{10}	10.04***	0.89	0.65	$\pi(F_{1-10})$	1.10	0.45	F_{1-10}	9.06	1.49	1.06***	84.10	17	17	13
$\omega = 5$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	41.35***	0.50	0.05	$\pi(F_{1-1})$	0.50	0.50	F_{1-1}	44.91	2.51	1.87***	56.72	31	26	17
F_2	8.20	0.22	0.05	$\pi(F_{1-2})$	0.55	0.05	F_{1-2}	33.87	2.26	1.57***	67.28	21	17	12
F_3	2.60	0.09	0.02	$\pi(F_{1-3})$	0.56	0.01	F_{1-3}	26.31	2.23	1.52***	70.16	20	16	13
F_4	1.81	0.08	0.03	$\pi(F_{1-4})$	0.56	0.01	F_{1-4}	22.17	2.22	1.51***	70.39	15	15	14
F_5	8.05**	0.38	0.15	$\pi(F_{1-5})$	0.68	0.12	F_{1-5}	18.49	2.02	1.30***	77.90	15	13	10
F_6	1.12	0.06	0.03	$\pi(F_{1-6})$	0.68	0.00	F_{1-6}	15.60	2.01	1.30***	77.95	17	17	9
F_7	1.49	0.09	0.04	$\pi(F_{1-7})$	0.69	0.01	F_{1-7}	13.27	2.01	1.32***	77.95	19	13	10
F_8	3.24	0.21	0.12	$\pi(F_{1-8})$	0.72	0.03	F_{1-8}	11.38	1.99	1.25***	78.83	13	13	10
F_9	13.24***	1.21	0.92	$\pi(F_{1-9})$	1.41	0.69	F_{1-9}	10.37	0.87	0.34	98.38	0	0	0
F_{10}	0.88	0.07	0.05	$\pi(F_{1-10})$	1.41	0.00	F_{1-10}	9.14	0.87	0.33	98.57	0	0	0

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Table IA.4 — Continued

	Panel A: Factors & Tangency Portfolios						Panel B: Two-Pass Statistics							
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
$\omega = 10$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	41.86***	0.51	0.05	$\pi(F_{1-1})$	0.51	0.51	F_{1-1}	44.93	2.50	1.68***	63.84	33	25	18
F_2	8.63	0.24	0.05	$\pi(F_{1-2})$	0.56	0.05	F_{1-2}	33.89	2.25	1.38***	73.50	19	19	12
F_3	2.81	0.09	0.03	$\pi(F_{1-3})$	0.57	0.01	F_{1-3}	26.32	2.23	1.33***	75.72	18	16	12
F_4	4.77	0.21	0.08	$\pi(F_{1-4})$	0.61	0.04	F_{1-4}	22.24	2.19	1.24***	77.61	22	18	11
F_5	8.60**	0.41	0.16	$\pi(F_{1-5})$	0.74	0.12	F_{1-5}	18.52	2.01	1.06***	84.53	17	16	10
F_6	1.40	0.07	0.03	$\pi(F_{1-6})$	0.74	0.00	F_{1-6}	15.64	2.01	1.06***	84.61	17	17	10
F_7	2.61	0.16	0.08	$\pi(F_{1-7})$	0.76	0.02	F_{1-7}	13.32	2.00	1.06***	84.84	18	17	8
F_8	9.82***	0.72	0.44	$\pi(F_{1-8})$	1.05	0.29	F_{1-8}	11.66	1.86	0.75***	92.20	17	9	3
F_9	12.31***	1.00	0.67	$\pi(F_{1-9})$	1.45	0.40	F_{1-9}	10.39	0.82	0.22	99.35	0	0	0
F_{10}	0.54	0.04	0.03	$\pi(F_{1-10})$	1.45	0.00	F_{1-10}	9.15	0.82	0.22	99.41	0	0	0
$\omega = 20$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	42.56***	0.52	0.05	$\pi(F_{1-1})$	0.52	0.52	F_{1-1}	44.97	2.49	1.39***	74.42	31	28	19
F_2	9.37	0.26	0.06	$\pi(F_{1-2})$	0.58	0.06	F_{1-2}	33.92	2.26	1.10***	82.21	21	17	13
F_3	3.22	0.11	0.03	$\pi(F_{1-3})$	0.59	0.01	F_{1-3}	26.36	2.24	1.05***	83.67	17	16	13
F_4	11.37***	0.57	0.24	$\pi(F_{1-4})$	0.82	0.23	F_{1-4}	22.71	2.05	0.76***	92.16	19	16	10
F_5	2.93	0.13	0.05	$\pi(F_{1-5})$	0.83	0.01	F_{1-5}	18.63	2.03	0.71***	92.51	21	17	8
F_6	2.17	0.12	0.05	$\pi(F_{1-6})$	0.84	0.01	F_{1-6}	15.75	2.03	0.70***	92.65	19	16	12
F_7	9.57***	0.64	0.36	$\pi(F_{1-7})$	1.06	0.22	F_{1-7}	13.71	1.97	0.53***	96.10	22	15	5
F_8	12.66***	0.94	0.59	$\pi(F_{1-8})$	1.42	0.36	F_{1-8}	12.17	1.12	0.20	99.49	0	0	0
F_9	5.76**	0.39	0.22	$\pi(F_{1-9})$	1.47	0.05	F_{1-9}	10.40	0.79	0.13	99.78	0	0	0
F_{10}	0.41	0.03	0.02	$\pi(F_{1-10})$	1.47	0.00	F_{1-10}	9.16	0.79	0.13	99.80	0	0	0

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Table IA.4 — Continued

	Panel A: Factors & Tangency Portfolios							Panel B: Two-Pass Statistics						
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
$\omega = 50$	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_{\epsilon}$	$\overline{\text{RMS}}_{\alpha}$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	43.46***	0.54	0.06	$\pi(F_{1-1})$	0.54	0.54	F_{1-1}	45.08	2.50	0.89***	89.22	29	25	17
F_2	10.76*	0.30	0.07	$\pi(F_{1-2})$	0.62	0.08	F_{1-2}	34.02	2.29	0.64***	93.23	22	17	13
F_3	4.28	0.14	0.04	$\pi(F_{1-3})$	0.64	0.02	F_{1-3}	26.47	2.27	0.60***	93.87	17	16	12
F_4	13.70***	0.74	0.33	$\pi(F_{1-4})$	0.98	0.34	F_{1-4}	23.00	2.08	0.32***	98.47	19	16	9
F_5	1.53	0.07	0.03	$\pi(F_{1-5})$	0.98	0.00	F_{1-5}	18.87	2.08	0.31***	98.49	22	16	8
F_6	5.14*	0.28	0.13	$\pi(F_{1-6})$	1.02	0.04	F_{1-6}	16.06	2.07	0.30***	98.69	13	11	8
F_7	13.58***	1.01	0.62	$\pi(F_{1-7})$	1.43	0.41	F_{1-7}	14.46	1.18	0.10**	99.89	0	0	0
F_8	5.62**	0.34	0.17	$\pi(F_{1-8})$	1.47	0.04	F_{1-8}	12.25	0.91	0.07	99.94	0	0	0
F_9	3.46	0.23	0.13	$\pi(F_{1-9})$	1.49	0.02	F_{1-9}	10.40	0.77	0.06	99.96	0	0	0
F_{10}	0.34	0.03	0.02	$\pi(F_{1-10})$	1.49	0.00	F_{1-10}	9.17	0.77	0.06	99.96	0	0	0

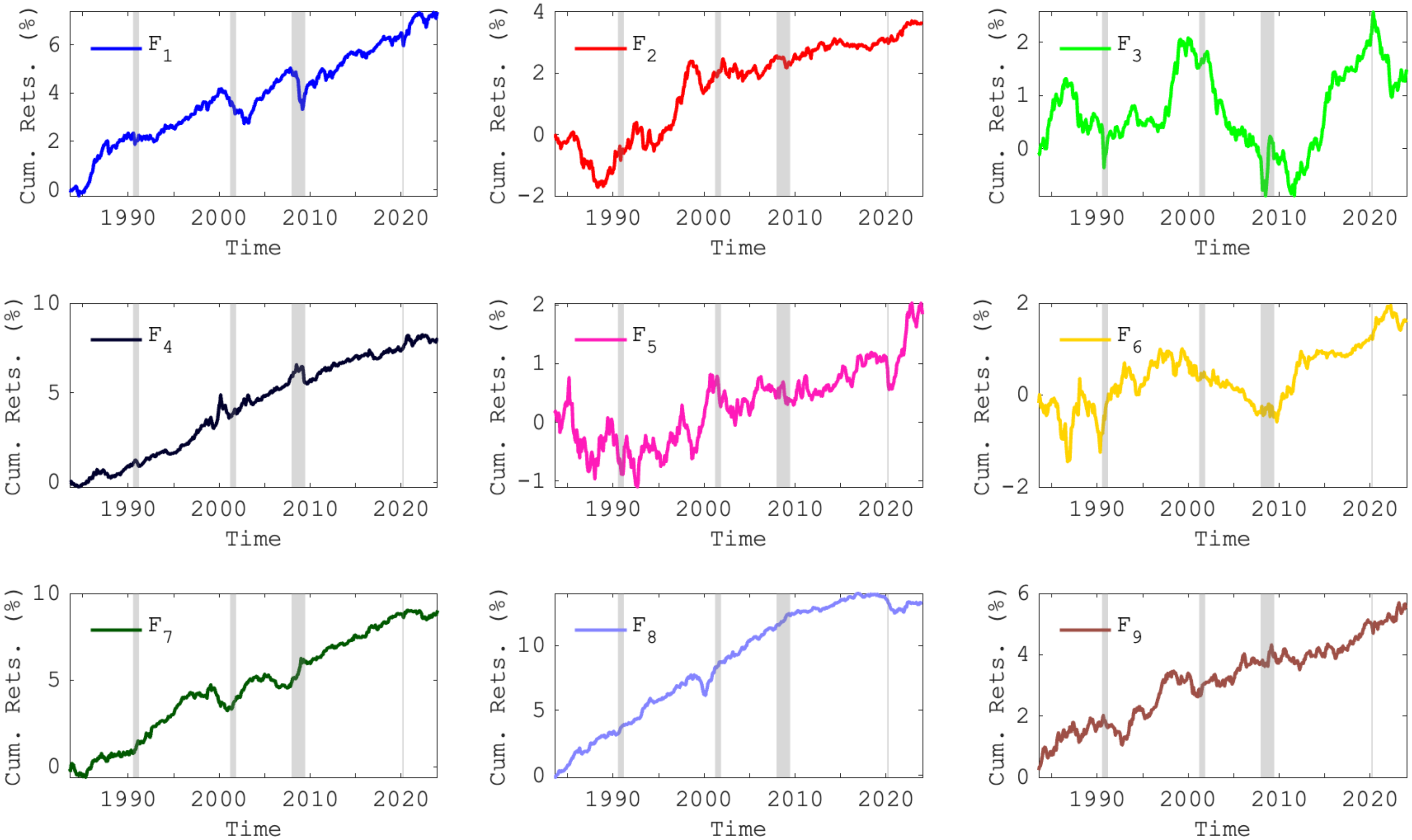

Figure IA.3. Latent Factor Cumulative Returns. The figure presents the cumulative sum of (log) returns of each of the nine latent factors entering the optimal pricing kernel. The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ to the 48 value and momentum portfolios of Asness et al. (2013) (see Table 1). Returns are normalized to have 10% annualized volatility. NBER recession periods are shaded in gray. The sample is monthly and covers the 07/1983–12/2023 period.

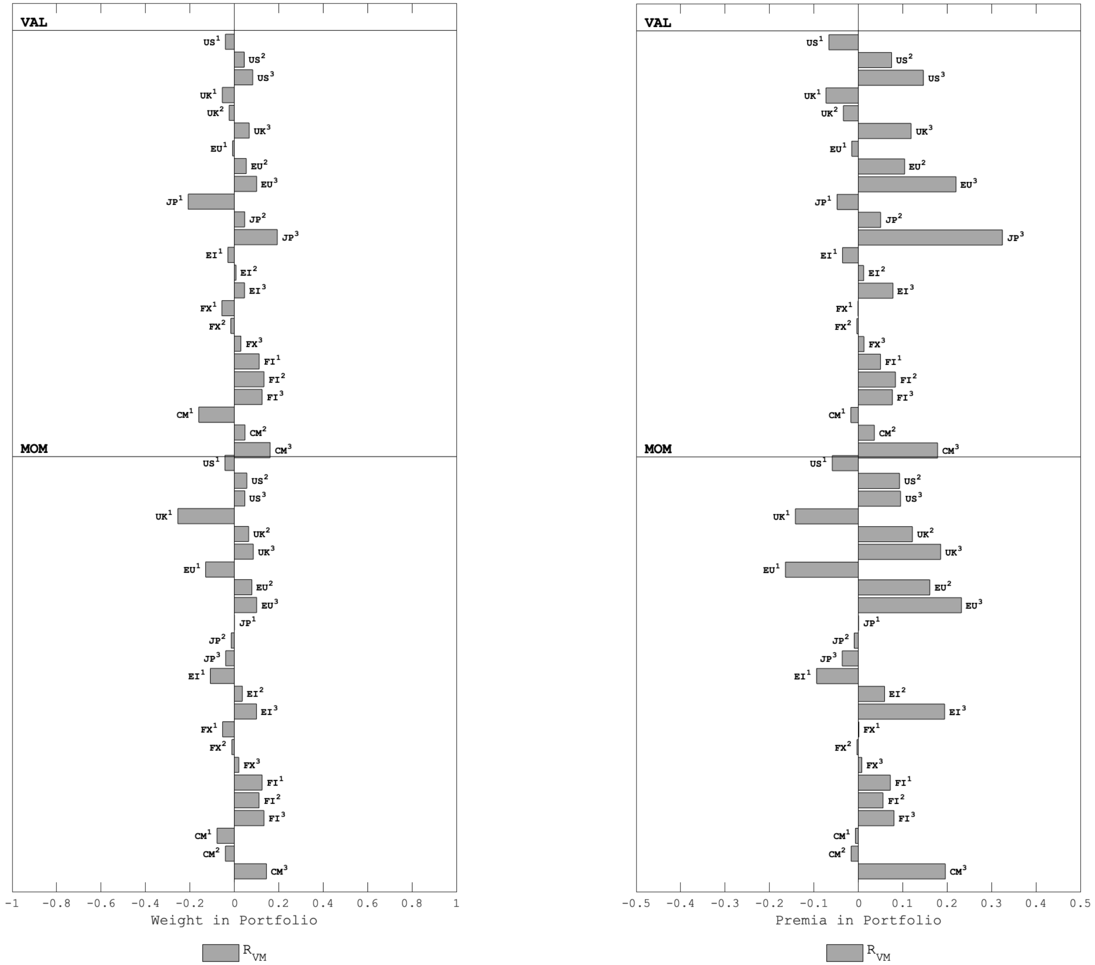

Figure IA.4. Tangency Portfolio Exposures to Test Assets. The figure displays the weight (left) and risk premium (right) of each of the 48 value and momentum test assets comprising the optimal nine-latent-factor tangency portfolio (R_{VM}). The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ to the 48 value and momentum portfolios of Asness et al. (2013) (see Table 1). The mean–variance weights of the latent factors are given by the inverse of the covariance matrix (diagonal, as the latent factors are orthogonal) multiplied by factor means ($\widehat{b} = \mu_F \Sigma_F^{-1}$). These weights are multiplied by their respective loadings and the original rotation matrix from the Gram-Schmidt orthogonalization procedure, thereby recovering the mapping of the latent factors directly to test asset excess returns. The left-hand panel displays the weights, scaled to sum to one. The right-hand panel displays the contributions in terms of premia, which are given by the weights multiplied by the respective average test asset excess returns, where the overall return is normalized to have a 10% annualized volatility. Top sub-panels correspond to value test assets, and the bottom to momentum portfolios.

IA.5.2 Stability Analysis

Figure IA.5 presents recursive estimates of the most parsimonious latent-factor model that eliminates all individual alphas in the cross-section of 48 value and momentum test assets of Asness et al. (2013).

[Figure IA.5 about here.]

IA.5.3 Spanning Evidence

Table IA.5 presents spanning regressions, in the sense of Barillas and Shanken (2017), of the latent factors (Panel A) and tangency portfolios of increasing dimensionality (Panel B) on the AMP '*everywhere*' factors, as well as their disaggregated components: '*stock selection*', including all individual stocks markets for the US, the UK, Continental Europe and Japan; and, '*asset allocation*', including equity index futures, government bonds, currencies, and commodity futures (see Table IA.1).

[Table IA.5 about here.]

Table IA.6 presents spanning regressions of the AMP '*everywhere*' factors, as well as their disaggregated '*stock selection*' and '*asset allocation*' components (see Table IA.1), on latent-factor tangency portfolios of increasing dimensionality.

[Table IA.6 about here.]

IA.5.4 Decomposition Evidence

Table IA.7 presents diagnostics of the latent factors extracted from each of (i) the 24 value test assets, and (ii) the 24 momentum test assets, separately, using RP-PCA with RP-weight $\omega = 20$.

[Table IA.7 about here.]

Figure IA.6 plots a dynamic conditional correlation (DCC) model applied to the orthogonalized nine-factor tangency portfolios extracted from each of (i) the 24 value test assets, and (ii) the 24 momentum test assets, separately. This DCC is fitted on the orthogonalized components of each strategy, extracted by spanning the value (momentum) tangency portfolio on the momentum (value) portfolio and taking the residuals. This is equivalent to stripping-out the common factor structure shared between the models, just as AMP form market-neutral factors, where the first latent factor is attributable to a level ("market") factor.

[Figure IA.6 about here.]

Table IA.5
Spanning Regressions of Latent Factors on AMP Factors (Full)

The table presents OLS spanning regressions of latent factors (Panel A) and tangency portfolios (Panel B) on the three tradable factors of Asness et al. (2013), and a constant (α), in the sense of Barillas and Shanken (2017). The factors and tangency portfolios are those estimated in Table 1. In Panel A, we regress the individual latent factors, F_k for $k = 1, \dots, 10$, on three set of AMP factors, including the market (MKT), value (VAL) and momentum (MOM), plus a constant. The factors include: (i) the 'everywhere' factors (EV); (ii) the 'stock selection' factors (SS); and, (iii) the 'asset allocation' factors (AA), all following AMP and reported in Table IA.1. We report the individual loadings of each tradable factor, as well as the R^2 (in percent). Specifically, the α shows the unexplained average return, while SR_α is the unexplained Sharpe ratio. The latter has the benefit of being scale invariant. In Panel B, we repeat the spanning analysis by replacing the latent factors with the tangency portfolios of increasing dimensionality, $\pi(F_{1-k})$ for $k = 1, \dots, 10$. The sample is monthly, from 07/1983–12/2023. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

Panel A: Latent Factor Returns

	SR_α	α	MKT	VAL_{EV}	MOM_{EV}	R^2	SR_α	α	MKT	VAL_{SS}	MOM_{SS}	R^2	SR_α	α	MKT	VAL_{AA}	MOM_{AA}	R^2
F_1	−0.06	−0.05	5.08***	0.54**	0.28	92.67	−0.05	−0.04	5.08***	0.27*	0.12	92.67	−0.04	−0.03	5.06***	0.25	0.27	92.60
F_2	0.06	0.08	−0.02	0.41	0.20	−0.35	0.08	0.11*	−0.06	0.00	−0.15	−0.34	0.05	0.06	−0.03	0.73*	0.85**	0.57
F_3	0.05	0.05	0.16	−1.00***	−0.16	3.00	0.06	0.06	0.13	−0.74***	−0.17	5.61	0.01	0.01	0.17	0.29	0.19	0.26
F_4	0.13	0.04***	0.18***	−0.70***	2.22***	79.81	0.09	0.03*	0.23***	−0.17**	1.33***	75.49	0.14	0.08***	0.05	−0.62***	1.92***	32.63
F_5	0.03	0.02	0.07	0.28	−0.11	0.61	0.06	0.04	0.03	−0.09	−0.26**	1.05	0.00	0.00	0.07	0.78**	0.38	1.57
F_6	0.01	0.01	0.08	−0.04	0.25	0.58	0.01	0.01	0.09	−0.06	0.19**	1.89	0.02	0.01	0.05	0.21	0.01	−0.16
F_7	0.14	0.07***	0.09	0.58***	0.06	4.54	0.18	0.09***	0.07	0.03	−0.07	0.73	0.13	0.06***	0.07	1.18***	0.13	11.92
F_8	0.13	0.05**	0.02	1.56***	0.93***	27.05	0.19	0.07***	0.02	0.88***	0.37***	32.90	0.23	0.10***	−0.03	0.39***	1.08***	12.91
F_9	0.02	0.01	−0.02	1.07***	0.65***	10.59	0.05	0.03	0.00	0.30***	0.38***	5.48	0.07	0.03	−0.09*	1.52***	0.16	20.05
F_{10}	−0.02	−0.01	0.03	0.22	0.13	0.08	−0.02	−0.01	0.03	0.20**	0.08	1.46	0.01	0.00	0.02	−0.19	0.12	0.54

Panel B: Tangency Portfolio Returns

	SR_α	α	MKT	VAL_{EV}	MOM_{EV}	R^2	SR_α	α	MKT	VAL_{SS}	MOM_{SS}	R^2	SR_α	α	MKT	VAL_{AA}	MOM_{AA}	R^2
$\pi(F_{1-1})$	−0.06	0.00	0.27***	0.03**	0.01	92.67	−0.05	0.00	0.27***	0.01*	0.01	92.67	−0.04	0.00	0.27***	0.01	0.01	92.60
$\pi(F_{1-2})$	0.02	0.00	0.27***	0.05*	0.03	73.58	0.05	0.00	0.27***	0.01	0.00	73.49	0.02	0.00	0.27***	0.06*	0.06**	73.72
$\pi(F_{1-3})$	0.04	0.00	0.28***	0.02	0.02	73.63	0.07	0.01	0.27***	−0.01	−0.01	73.59	0.03	0.00	0.28***	0.06**	0.07**	74.02
$\pi(F_{1-4})$	0.12	0.01**	0.32***	−0.14***	0.54***	77.33	0.11	0.01**	0.33***	−0.05**	0.31***	73.81	0.14	0.02***	0.29***	−0.08	0.52***	55.98
$\pi(F_{1-5})$	0.12	0.01**	0.32***	−0.13***	0.54***	74.76	0.12	0.01**	0.33***	−0.05**	0.29***	71.00	0.13	0.02***	0.29***	−0.04	0.54***	55.54
$\pi(F_{1-6})$	0.12	0.01**	0.33***	−0.13***	0.55***	75.78	0.12	0.02**	0.33***	−0.05***	0.30***	72.85	0.14	0.02***	0.29***	−0.03	0.54***	55.00
$\pi(F_{1-7})$	0.18	0.04***	0.36***	0.08	0.57***	46.65	0.22	0.05***	0.36***	−0.04	0.28***	47.37	0.19	0.04***	0.32***	0.39***	0.59***	38.36
$\pi(F_{1-8})$	0.22	0.07***	0.37***	1.00***	1.12***	38.85	0.27	0.09***	0.37***	0.47***	0.49***	29.35	0.31	0.10***	0.30***	0.62***	1.22***	34.18
$\pi(F_{1-9})$	0.22	0.07***	0.36***	1.24***	1.26***	42.41	0.28	0.10***	0.37***	0.54***	0.58***	31.11	0.31	0.11***	0.28***	0.95***	1.26***	32.28
$\pi(F_{1-10})$	0.22	0.07***	0.36***	1.24***	1.27***	42.60	0.28	0.10***	0.37***	0.54***	0.58***	31.32	0.31	0.11***	0.28***	0.95***	1.26***	32.34

Table IA.6

Spanning Regressions of AMP Factors on Latent Factor Tangency Portfolios (Full)

The table presents OLS spanning regressions of each of the full set of tradable factors of Asness et al. (2013) on the latent-factor tangency portfolio in the sense of Barillas and Shanken (2017). Specifically, we regress each of the AMP factors — value (VAL) and momentum (MOM) — on the tangency portfolios comprising an increasing number of latent factors, $\pi(F_{1-k})$ for $k = 1, \ldots, 10$, plus a constant. The AMP factors include: (i) the 'everywhere' factors (EV); (ii) the 'stock selection' factors (SS); and, (iii) the 'asset allocation' factors (AA), all following AMP and reported in Table IA.1. The tangency portfolios are those estimated using RP-PCA with baseline RP-weight $\omega = 20$ (see Table 1). For each regression, we report the constant (α), the exposure (β), and the R^2 (in percent). Importantly, the α represents the part of the average excess return of the selected AMP factor unspanned by the tangency portfolio. A significant α means that the information in the AMP factor is not entirely subsumed by the tangency portfolio. We also report SR_α, i.e. the unexplained Sharpe ratio. The sample is monthly, from 07/1983–12/2023. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

		$\pi(F_{1-1})$	$\pi(F_{1-2})$	$\pi(F_{1-3})$	$\pi(F_{1-4})$	$\pi(F_{1-5})$	$\pi(F_{1-6})$	$\pi(F_{1-7})$	$\pi(F_{1-8})$	$\pi(F_{1-9})$	$\pi(F_{1-10})$
VAL_{EV}	SR_α	0.13	0.13	0.13	0.27	0.27	0.27	0.21	0.10	0.08	0.08
	α	0.03**	0.03**	0.03**	0.05***	0.05***	0.05***	0.04***	0.02	0.02	0.02
	β	0.05	0.06	0.03	−0.38***	−0.36***	−0.36***	−0.14***	0.04	0.07**	0.07**
	R^2	−0.05	0.08	−0.15	20.26	18.44	18.92	4.64	0.50	1.80	1.84
MOM_{EV}	SR_α	0.17	0.17	0.17	0.03	0.03	0.03	0.05	0.04	0.03	0.03
	α	0.04***	0.04***	0.04***	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	β	−0.28**	−0.22**	−0.20*	0.50***	0.47***	0.48***	0.24***	0.15***	0.15***	0.15***
	R^2	2.85	2.28	1.84	24.34	22.39	23.12	9.07	6.77	6.92	6.92
VAL_{SS}	SR_α	0.09	0.09	0.10	0.22	0.22	0.22	0.20	0.05	0.05	0.04
	α	0.04	0.03	0.04*	0.08***	0.08***	0.08***	0.07***	0.02	0.02	0.02
	β	0.04	0.07	−0.03	−0.72***	−0.69***	−0.70***	−0.40***	0.11*	0.10*	0.11**
	R^2	−0.18	−0.12	−0.19	19.05	17.90	18.97	9.56	1.04	1.09	1.16
MOM_{SS}	SR_α	0.16	0.16	0.16	0.02	0.02	0.02	0.04	0.07	0.05	0.05
	α	0.07***	0.07***	0.07***	0.01	0.01	0.01	0.01	0.03	0.02	0.02
	β	−0.60***	−0.54***	−0.48**	0.81***	0.76***	0.78***	0.41***	0.14**	0.17***	0.17***
	R^2	4.29	4.24	3.45	19.82	17.65	18.91	8.34	1.46	2.71	2.67
VAL_{AA}	SR_α	0.12	0.12	0.12	0.19	0.18	0.18	0.11	0.13	0.08	0.09
	α	0.02**	0.02**	0.02**	0.03***	0.03***	0.03***	0.02**	0.02**	0.01	0.01
	β	0.06	0.06	0.06	−0.15***	−0.13***	−0.12***	0.03	0.00	0.04**	0.04**
	R^2	0.10	0.20	0.26	4.66	3.77	3.42	0.13	−0.20	0.96	0.92
MOM_{AA}	SR_α	0.13	0.12	0.12	0.03	0.03	0.03	0.06	−0.04	−0.02	−0.02
	α	0.02***	0.02***	0.02***	0.01	0.01	0.01	0.01	−0.01	0.00	0.00
	β	−0.05	−0.01	−0.01	0.29***	0.28***	0.27***	0.12***	0.17***	0.13***	0.14***
	R^2	0.00	−0.20	−0.20	14.43	14.10	13.57	4.05	14.64	10.22	10.34

Table IA.7
Separate Value and Momentum Tangency Portfolio Diagnostics

The table presents model diagnostics of the first two steps of the three-pass asset pricing procedure of Giglio and Xiu (2021). Specifically, we examine the properties of the latent factors and associated tangency portfolios (Panels A C), and the performance of the latent-factor models (Panels B and D). We do so by examining the first ten latent factors, i.e., F_k for $k = 1, 2, \dots, 10$, and models including an increasing number of latent factors. We estimate the latent factors applying the RP-PCA method of Lettau and Pelger (2020a,b) with RP-weight of $\omega = 20$ to each of (i) 24 value, and (ii) 24 momentum test asset returns, separately. Specifically, Panels A1 and C1 show the annualized average return of each latent factor (μ_{F_k}), where ***, ** and * indicate statistical significance at the 1%, 5% and 10% confidence levels, respectively, based on Newey and West (1987) standard errors; the k-th factor's Sharpe ratio (SR); and, the k-th factor's weight in the tangency portfolio ($\widehat{b}_{MV} = \mu_F {\Sigma_F}^{-1}$). Panels A2 and C2 present the annualized maximum Sharpe ratio of the tangency portfolios (SR), and the change in the Sharpe ratio owing to the inclusion of the next additional latent factor, k (ΔSR). Panels B and D provide several statistics and evaluation criteria for the first-pass (Equation (7): $\tilde{X}_{nt} = \tilde{F}_t \psi_n^\top + \epsilon_{nt}$) and second-pass (Equation (8): $\overline{X}_n = \widehat{\psi}_n \gamma^\top + a_n$) regressions, where X are the test asset returns, ψ are the asset risk exposures, and γ are the latent factor prices of risk (which, by no arbitrage equal the factor average returns). Panels B1 and D1 report the average idiosyncratic variance ($\overline{\sigma}_\epsilon^2 = 1/N \sum_{n=1}^{N} [Var(\widehat{\epsilon}_n)/Var(X_n)]$), and the average root-mean-square alpha (pricing error) from the time-series regressions ($\overline{\text{RMS}}_\alpha = \sqrt{\widehat{\alpha}\widehat{\alpha}'/N}$). Panels B2 and D2 show the mean absolute pricing error from the cross-sectional regression (MAE), and the percentage of variation explained by the tangency portfolio (R^2). Panels B3 and D3 present the number of individually statistically significant alphas for each factor model. The statistical significance of individual alphas and mean absolute pricing errors are estimated using a wild bootstrap procedure similar to that of Giglio et al. (2021), where multiple-hypothesis testing biases are addressed via the Benjamini and Hochberg (1995, BH) false discovery control approach. Thus, $\alpha_{\xi\%}^{BH}$ represents the number of individually significant pricing errors at the BH-corrected $\xi = \{10\%, 5\%, 1\%\}$ levels, respectively. See Section IA.2.3, in the Internet Appendix, for details of the wild bootstrap algorithm. The sample spans the 07/1983–12/2023 period, return data are at monthly frequency.

	Panel A: Factors & Tangency Portfolios						Panel B: Two-Pass Statistics							
	A1: Factors				A2: Tangency Portfolios			B1: First-Pass		B2: Second-Pass		B3: Pricing Errors		
VAL	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}_\epsilon^2$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha_{10\%}^{\text{BH}}$	$\alpha_{5\%}^{\text{BH}}$	$\alpha_{1\%}^{\text{BH}}$
F_1	30.74***	0.54	0.08	$\pi(F_{1-1})$	0.54	0.54	F_{1-1}	44.99	2.01	1.02***	82.74	8	8	5
F_2	5.76	0.23	0.07	$\pi(F_{1-2})$	0.59	0.04	F_{1-2}	33.81	1.73	0.85***	88.81	8	6	6
F_3	1.43	0.07	0.03	$\pi(F_{1-3})$	0.59	0.00	F_{1-3}	25.78	1.71	0.85***	89.49	10	6	6
F_4	4.67*	0.30	0.16	$\pi(F_{1-4})$	0.66	0.07	F_{1-4}	21.52	1.56	0.69***	93.25	8	7	4
F_5	3.61	0.24	0.13	$\pi(F_{1-5})$	0.70	0.04	F_{1-5}	17.64	1.45	0.63***	95.03	8	7	3
F_6	0.95	0.07	0.04	$\pi(F_{1-6})$	0.71	0.00	F_{1-6}	14.49	1.45	0.63***	95.03	8	4	0
F_7	2.79	0.21	0.14	$\pi(F_{1-7})$	0.74	0.03	F_{1-7}	11.57	1.39	0.58***	95.86	7	4	4
F_8	4.86***	0.46	0.37	$\pi(F_{1-8})$	0.87	0.13	F_{1-8}	9.63	1.16	0.42**	97.71	0	0	0
F_9	4.30***	0.47	0.42	$\pi(F_{1-9})$	0.99	0.12	F_{1-9}	8.16	0.87	0.26	98.99	0	0	0

(*continued over page*)

Table IA.7 — Continued

	Panel C: Factors & Tangency Portfolios						Panel D: Two-Pass Statistics							
	C1: Factors				C2: Tangency Portfolios			D1: First-Pass		D2: Second-Pass		D3: Pricing Errors		
MOM	$\mu_{F,k}$	SR	$\widehat{b}_{MV,k}$		SR	ΔSR		$\widehat{\sigma}^2_\epsilon$	$\overline{\text{RMS}}_\alpha$	MAE	R^2	$\alpha^{\text{BH}}_{10\%}$	$\alpha^{\text{BH}}_{5\%}$	$\alpha^{\text{BH}}_{1\%}$
F_1	29.42***	0.50	0.07	$\pi(F_{1-1})$	0.50	0.50	F_{1-1}	44.64	2.86	1.74***	67.01	18	16	12
F_2	8.63**	0.33	0.11	$\pi(F_{1-2})$	0.60	0.10	F_{1-2}	33.65	2.56	1.26***	80.06	13	10	6
F_3	10.34***	0.53	0.23	$\pi(F_{1-3})$	0.81	0.20	F_{1-3}	27.44	1.89	0.67***	95.45	6	6	5
F_4	6.78**	0.34	0.14	$\pi(F_{1-4})$	0.87	0.07	F_{1-4}	20.92	1.40	0.49*	97.49	3	2	0
F_5	1.43	0.09	0.05	$\pi(F_{1-5})$	0.88	0.00	F_{1-5}	16.86	1.38	0.48*	97.63	2	2	0
F_6	1.27	0.09	0.06	$\pi(F_{1-6})$	0.88	0.00	F_{1-6}	13.95	1.36	0.46	97.69	4	1	0
F_7	2.10	0.17	0.11	$\pi(F_{1-7})$	0.90	0.02	F_{1-7}	11.41	1.32	0.45	98.06	3	2	0
F_8	3.80**	0.33	0.24	$\pi(F_{1-8})$	0.96	0.06	F_{1-8}	9.27	1.15	0.36	98.55	0	0	0
F_9	2.15	0.21	0.16	$\pi(F_{1-9})$	0.98	0.02	F_{1-9}	7.52	1.09	0.33	98.86	0	0	0

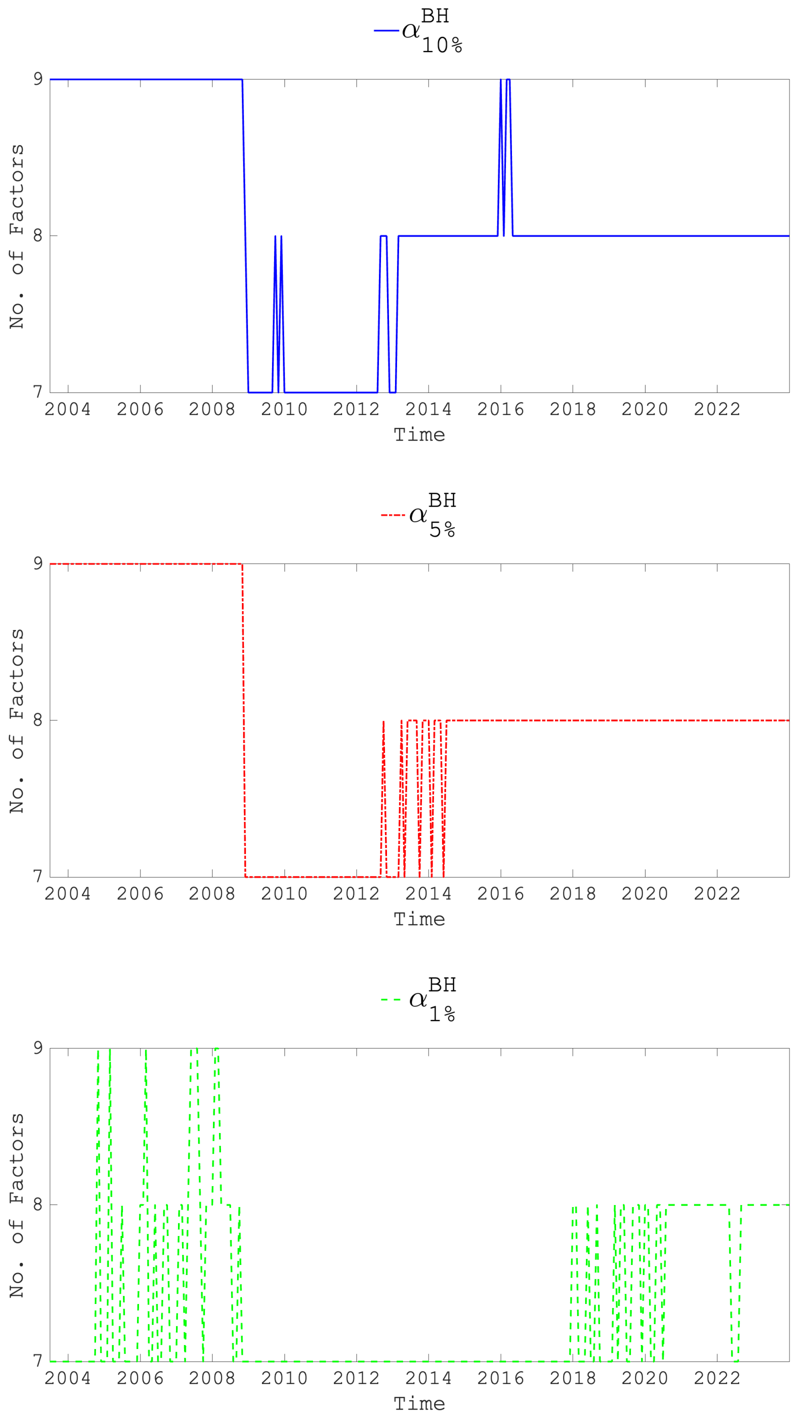

Figure IA.5. Pricing Error Recursive Stability (Factors). The figure presents recursive estimates of the most parsimonious latent-factor model required to completely eliminate all individual pricing errors, α, in the cross-section of 48 value and momentum test asset returns. Latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ to the 48 value and momentum test assets (see Table 1). We estimate the number of individually significant alphas using a wild bootstrap procedure similar to that of Giglio et al. (2021), where multiple-hypothesis testing biases are addressed via the Benjamini and Hochberg (1995, BH) false discovery control approach. Thus, α_{ξ}^{BH} represents the the BH-corrected $\xi = \{10\%, 5\%, 1\%\}$ levels, respectively. See Section IA.2.3, in the Internet Appendix, for further details of the wild bootstrap algorithm. We use an initial expanding window of 20 years, where the full sample is monthly from 07/1983–12/2023. The sample period displayed is from 07/2003–12/2023.

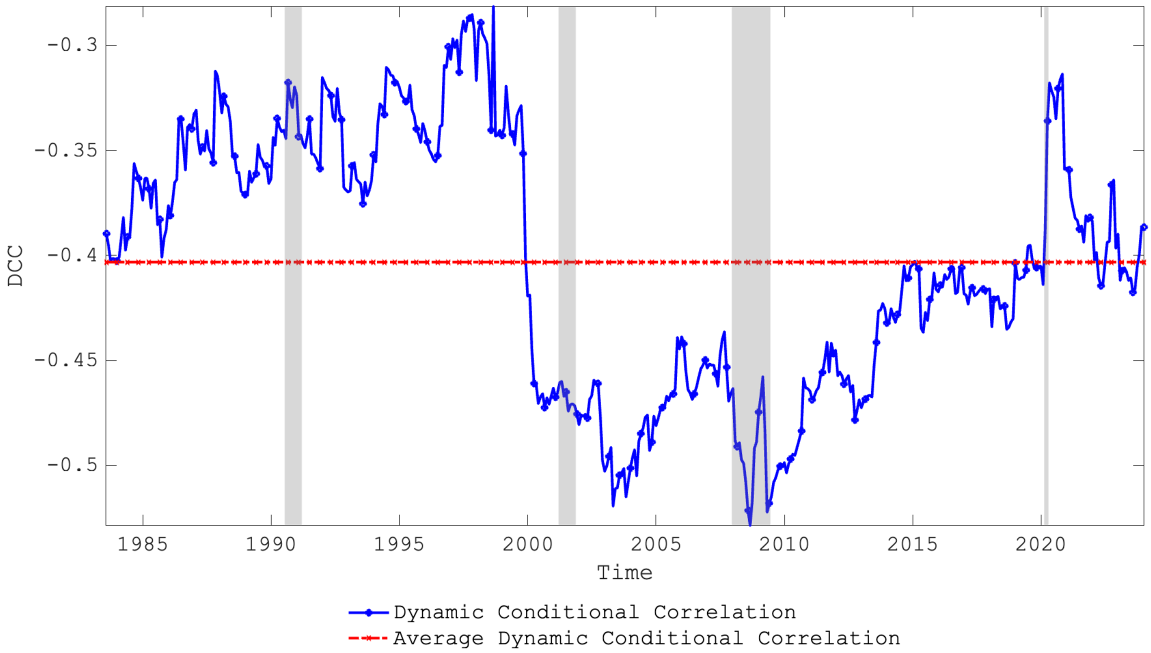

Figure IA.6. Dynamic Conditional Correlation. The figure plots the dynamic conditional correlation (DCC) model of Engle (2002) applied to the orthognalized components of the individual nine-latent-factor value and momentum tangency portfolio returns. Separate value and momentum tangency portfolios are obtained by applying RP-PCA with RP-weight $\omega = 20$ to the 24 value and 24 momentum test asset returns, respectively (see Table IA.7). Residuals from spanning regressions of the value tangency portfolio, π_V, on the momentum tangency portfolio, π_M, and vice versa, yield estimates of the information not shared across these two separate factor structures. The DCC of these residual components is plotted (blue), as well as the average DCC estimate (red). NBER recessions are shaded in gray. The sample is 07/1983–12/2023, at monthly frequency.

IA.5.5 Simulation Analysis

In this section, we use Monte Carlo simulations to examine the dominance of forming the tangency portfolio from combining (with mean–variance weights) latent factors extracted from the joint cross-section of value and momentum test assets ($N = 48$), in contrast to combining (again, using mean–variance weights) the two value and momentum tangency portfolios extracted separately from the value ($N = 24$) and momentum ($N = 24$) cross-sections, respectively.

We set up the simulation exercise similar to that of Giglio and Xiu (2021, GX) and Nucera et al. (2024, NSZ). However, unlike these studies, we use the latent factors themselves, rather than the de-noised tradable factors, in the data generating process (DGP) driving the value and momentum portfolio returns.[10] Therefore, we work directly with the latent factors, without having to determine which de-noised tradable factors (e.g., HML factors) drive the DGP. Specifically, as with the wild bootstrapped alpha tests, we use the ten latent factors extracted using RP-PCA with a baseline RP-weight of 20. Thus, the DGP includes the nine factors necessary for achieving full spanning and entering the optimal SDF, plus an extra factor. This is consistent with the GX and NSZ findings that it is generally preferable to include slightly more factors than fewer in the SDF. In the simulation in particular, it is crucial that the moments of the simulated test assets closely match those of the observed test assets. As will be shown later, this DGP performs rather well, which makes the simulation results reliable.

From this DGP, we simulate both value and momentum excess returns and then construct the four tangency portfolios: π_{VM} (from 48 test assets); π_V (from 24 value test assets); π_M (from 24 momentum test assets); and, $\pi_{V/M}$, a mean–variance weighted combination of π_V and π_M. We then compare the Sharpe ratios of these four tangency portfolios. We repeat these steps 10,000 times to obtain empirical distributions of the Sharpe ratios of the four tangency portfolios.

In short, we find that π_{VM} consistently outperforms $\pi_{V/M}$. The superior performance of π_{VM} over $\pi_{V/M}$ is highly statistically significant, with very few cases in which π_{VM} underperforms $\pi_{V/M}$ occurring in the very lowest tail of the distribution. This simulation analysis therefore lends strong support to the in-sample evidence showing the asset allocation benefits in combining factors extracted from the joint value and momentum cross-section relative to combining value and momentum factors extracted from the two separate cross-sections. Only by estimating factors and hence the tangency portfolio from the joint cross-section can one fully exploit the risk-return trade-off in value and momentum test assets, thereby achieving a superior efficient frontier. These benefits are instead foregone if factors are constructed from the individual value and momentum cross-sections and then used as separate pricing factors, as is typically the case in asset pricing. Indeed, it is this additional performance of π_{VM} over $\pi_{V/M}$ that allows us to eliminate all alphas, or *leftovers*, in value and momentum everywhere asset returns. Overall, the simulation results enable us to eliminate the possibility that the superior performance of π_{VM} over $\pi_{V/M}$ is sample-specific.

[10] For example, the reduced-form DGP in NSZ is driven by the de-noised tradable dollar, carry, momentum, and value factors cleaned using four latent factors. Their reduced-form DGP is observationally equivalent to using the four latent factors.

IA.5.5.1 DGP, Calibration, and Simulation

We simulate test asset excess returns, X_{nt}, using a ten-factor DGP, where factors are the latent factors, extracted from the cross-section of ($N = 48$) value and momentum test asset excess returns, using RP-PCA with RP-weight $\omega = 20$ (as in the main analysis). Specifically, we obtain the $K \times T$ latent factors (F_t) and risk exposures (Λ) using:

$$\min_{F,\Lambda} \left\{ \underbrace{\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{nt} - F_t \Lambda_n^{\top})^2}_{\text{TS: unexplained variation}} + \omega \underbrace{\frac{1}{N} \sum_{i=1}^{N} (\overline{X}_n - \overline{F} \Lambda_n^{\top})^2}_{\text{CS: pricing error}} \right\}, \tag{IA.13}$$

The DGP driving the test asset excess returns is given by

$$X_{nt} = \widehat{F}_t \widehat{\mathrm{B}}_n^{\top} + \epsilon_{nt}, \qquad n = 1, \ldots, 48, \ t = 1, \ldots, T, \tag{IA.14}$$

where X_{nt} is the time-t excess return on test asset n, $\widehat{\mathrm{B}}_n$ is the asset vector of estimated risk exposures to the ten estimated latent factors, $\widehat{F}_t$, and ϵ_{nt} captures the asset idiosyncratic risk.

To obtain the simulated test assets from this DGP, we draw the factors, risk exposures, and residuals using multivariate normal distributions. The multivariate normal distribution of the factors is calibrated to the means and covariance matrix of the ten latent factors extracted via RP-PCA (Equation (IA.13)). To draw the risk exposures, we need to obtain estimates of their variance-covariance, which are not available from the RP-PCA estimator. Therefore, we estimate N OLS regressions of the test asset returns on the extracted latent factors. However, we first transform the test assets and factors as in LP, to ensure that the risk exposure estimates match those obtained via RP-PCA (this adjustment would be unnecessary if factors were extracted via PCA); refer to the main text for the exact transformation. We then recover the residuals, or idiosyncratic risk, of a generic test asset n as $X_{nt} - \widehat{F}_t \widehat{\mathrm{B}}_n^{\top}$. Doing this for $n = 1, \ldots, N$, we then obtain the variance-covariance matrix of the panel of residuals. We draw the residuals from multivariate normal distributions imposing the means equal to zero and a diagonal variance-covariance matrix, by setting to zero the off-diagonal entries. Thus, the DGP assumes uncorrelated residuals across test assets.[11] The remaining steps of the Monte Carlo simulations are then outlined below. Here we note that we perform two sets of simulations: one with $T = 486$ (which matches the number of months in the actual return data), and one with $T = 1000$, to assess how results vary with larger T.

Step 1. We simulate test asset returns from the DGP process. For the generic θ^{th} Monte Carlo replication, we generate the artificial realizations of the variables $F_t^{(\theta)}$, $\mathrm{B}^{(\theta)}$, and $\epsilon_t^{(\theta)}$, respectively, from the multivariate normal distributions, calibrated as explained before. Using these realizations, we construct artificial test asset excess returns, $X_{nt}^{(\theta)}$, as

$$X_{nt}^{(\theta)} = \widehat{F}_t^{(\theta)} \mathrm{B}_n^{(\theta),\top} + \epsilon_{nt}^{(\theta)}, \qquad n = 1, \ldots, 48, \ t = 1, \ldots, T.$$

[11] All results are robust to simulating residuals given (i) zero mean and the full true covariance matrix, and (ii) true means and the full covariance matrix.

Hereafter, we omit the nt subscript notation for brevity.

Step 2. Using $X^{(\theta)}$, we estimate the four tangency portfolios, and their Sharpe ratios, following the same steps as in the empirical analysis. Thus, apply RP-PCA with RP-weight of 20 to the joint value and momentum cross-section $X^{(\theta)}$, to the value cross-section $X_V^{(\theta)}$, and to the momentum cross-section $X_M^{(\theta)}$. From each of the three cross-sections, we estimate nine latent factors; recall that, in the empirical analysis, we demonstrated that nine was the optimal number of factors for each of the three optimal SDFs. Next, with these three separate nine latent-factor models, we form the three corresponding tangency portfolios: (i) value–momentum, π_{VM}; (ii) value, π_V; and (iii) momentum, π_M, by combining the factors using mean–variance weights (multiplying factor means by the inverse of the covariance matrix). From this, we calculate the Sharpe ratio of π_{VM}, as well as the separate Sharpe ratios of π_V and π_M. We then obtain $\pi_{V/M}$ by combining the separate π_V and π_M tangency portfolios again using mean-variance weights, and compute its Sharpe ratio.

We iterate on steps 1 and 2 for $\Theta = 10,000$ times. We then examine the empirical distributions of the Sharpe ratios of the four tangency portfolios.

IA.5.5.2 Simulation Outputs

To start with, we check that the moments and Sharpe ratios of the simulated individual test asset excess returns match those of the true test assets. This turns out to be the case. Indeed, Figure IA.7 shows that the average of the test asset means, covariances, and Sharpe ratios closely resemble those in the data. Essentially, all values lie on a 45-degree line, with very small deviations. In the figure, we report results for the simulations implemented with $T = 486$. Thus, on average, we do not find any systematic upward or downward bias in the simulated moment and Sharpe ratio estimates. This suggests that the simulated test assets inherit the properties of the true test assets.

[Figure IA.7 about here.]

Figure IA.8, in the upper panels, displays the distributions of the Sharpe ratios (SRs) attributable to π_{VM}, $\pi_{V/M}$, π_V, and π_M. Lower panels display the distributions of the differences in the SRs between π_{VM} and each of the other three tangency portfolio SRs. The mean values of the SRs (absolute or in differences) are presented in the legends of the corresponding panels. Left panels refer to the simulations with $T = 486$ and right panels to those with $T = 1000$.

[Figure IA.8 about here.]

Using $T = 486$, the average SR of π_{VM} is 1.51, being only slightly higher than that observed in the true data for the nine latent-factor model (1.47). We also see that the SRs of $\pi_{V/M}$, π_V and π_M are 1.26, 1.05 and 1.09, again slightly higher than their in-sample counterparts (1.18, 0.99, and 0.98, respectively), suggesting a small upward bias in the simulation estimates. The absolute distance between the SRs of the simulated data and those of the true data reduces when using $T = 1000$, with no clear pattern evident (some being below and other above their true values). Nevertheless, the figure clearly shows that the distribution of the SRs of π_{VM} is shifted to the right compared to $\pi_{V/M}$, which is in turn to the right of those of π_V or π_M.

To better determine the difference in the SRs and, in particular, the outperformance of π_{VM}, we turn to the lower panels. The average of the difference in SRs between π_{VM} and $\pi_{V/M}$ is 0.25 (versus 0.29 in-sample), with the distribution almost strictly positive. Indeed, only 29 out of the 10,000 simulations (0.29%) delivers a SR of $\pi_{V/M}$ greater than π_{VM}. The difference in the SRs is evidently even larger when considering π_V and π_M (0.47 and 0.42, respectively). When increasing T to 10000, we see that the spread between the SRs of π_{VM} and $\pi_{V/M}$ widens slightly to 0.27, moving closer to the in-sample one. At the same time, the overperformance of π_{VM} relative to π_V increases to 0.50, while the difference with momentum remains unchanged.

To conclude the simulation analysis, in Figure IA.9, we decompose the SR of the tangency portfolio π_{VM} into the SRs of the spanned and unspanned components, using the spanning regressions as described in Section IV.D in the main text. Specifically, for each repetition, we regress π_{VM} on $\pi_{V/M}$ – scaled by their respective standard deviations – to recover the SRs attributable to the spanned (or intra) component, R_S, and the unspanned (or inter) component, R_U. The top left panel of Figure IA.9 shows the distributions of the SRs of R_S (red) and R_U (blue) using $T = 486$. The average estimates are 1.05 and 0.46, respectively, which are slightly higher (lower) than the in-sample estimate of R_S (R_U). Increasing T to 1000 (top right panel), as expected, brings the estimates of R_S and R_U on simulated data closer to the sample estimates: the SRs (shares) of R_S and R_U are 0.95 and 0.49 (66% and 34%), respectively. As shown in Table 5, the empirical estimates for R_S and R_U were 0.96 versus 0.51, respectively. As a result, on the simulated data too, we find that R_U accounts for a significant proportion of the SR of the value and momentum optimal tangency portfolio π_{VM}, amounting to roughly one third (see bottom left panel).

[Figure IA.9 about here.]

Summing up, this simple simulation exercise confirms the outperformance of π_{VM} over $\pi_{V/M}$. This lends support to the finding that combining value and momentum test assets flexibly, to construct the factors entering the tangency portfolio, leads to a better risk-return trade-off than that achieved by combining the two separate value and momentum tangency portfolios. Put simply, there is valuable information in the *inter* value and momentum factors, which is foregone by combining solely the *intra* value and momentum factors.

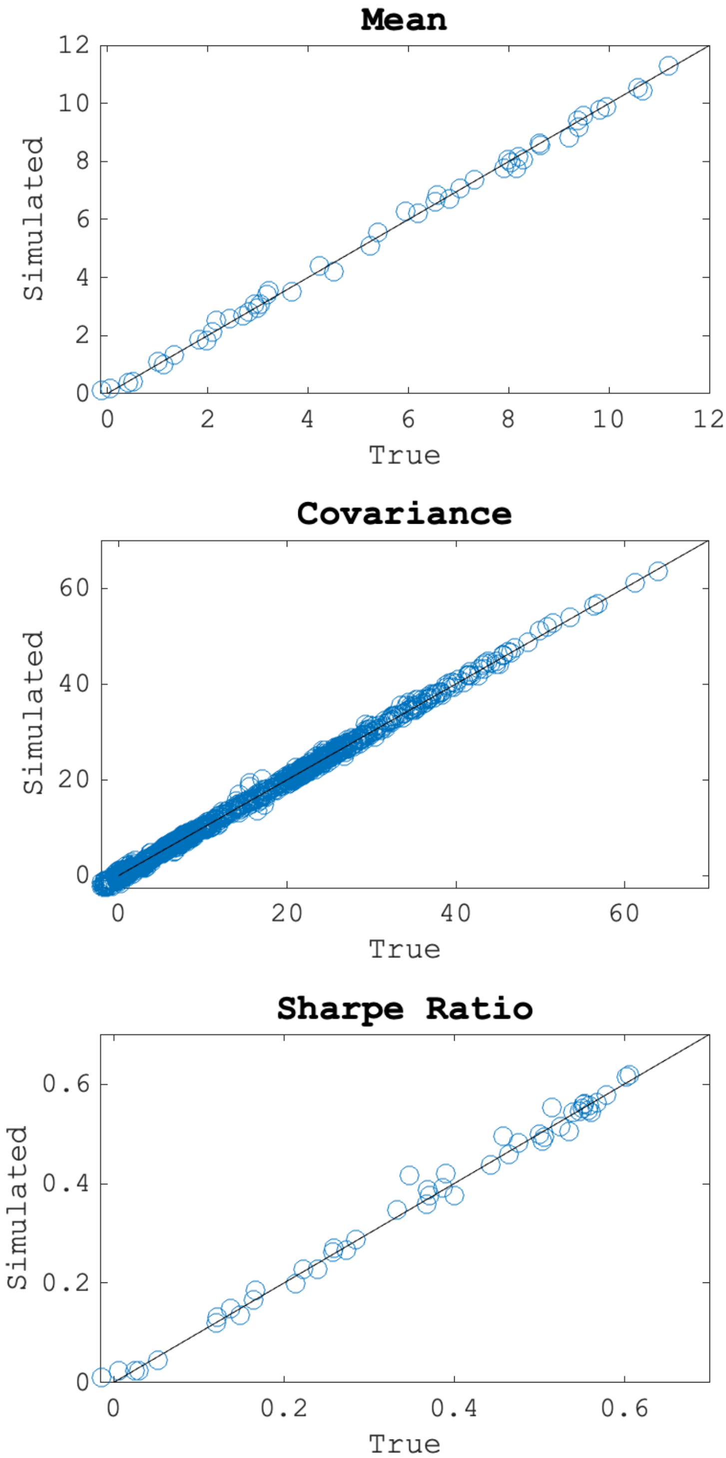

Figure IA.7. Simulated vs. True Test Asset Moments. The figure plots the average simulated test assets means (top panel), covariances (middle panel) and Sharpe ratios (bottom panel) across $\Theta = 10{,}000$ Monte Carlo simulations of value and momentum everywhere test asset excess returns, against their true observed sample moments. The DGP uses a ten-latent-factor model, extracted from the true 48 value and momentum test assets using RP-PCA with RP-weight $\omega = 20$. Parameters are calibrated to the first and second moments of the latent factors and loadings, as well as the block-diagonal of the covariance matrix of the residuals. The sample period of the raw test assets is 07/1983–12/2023, at monthly frequency.

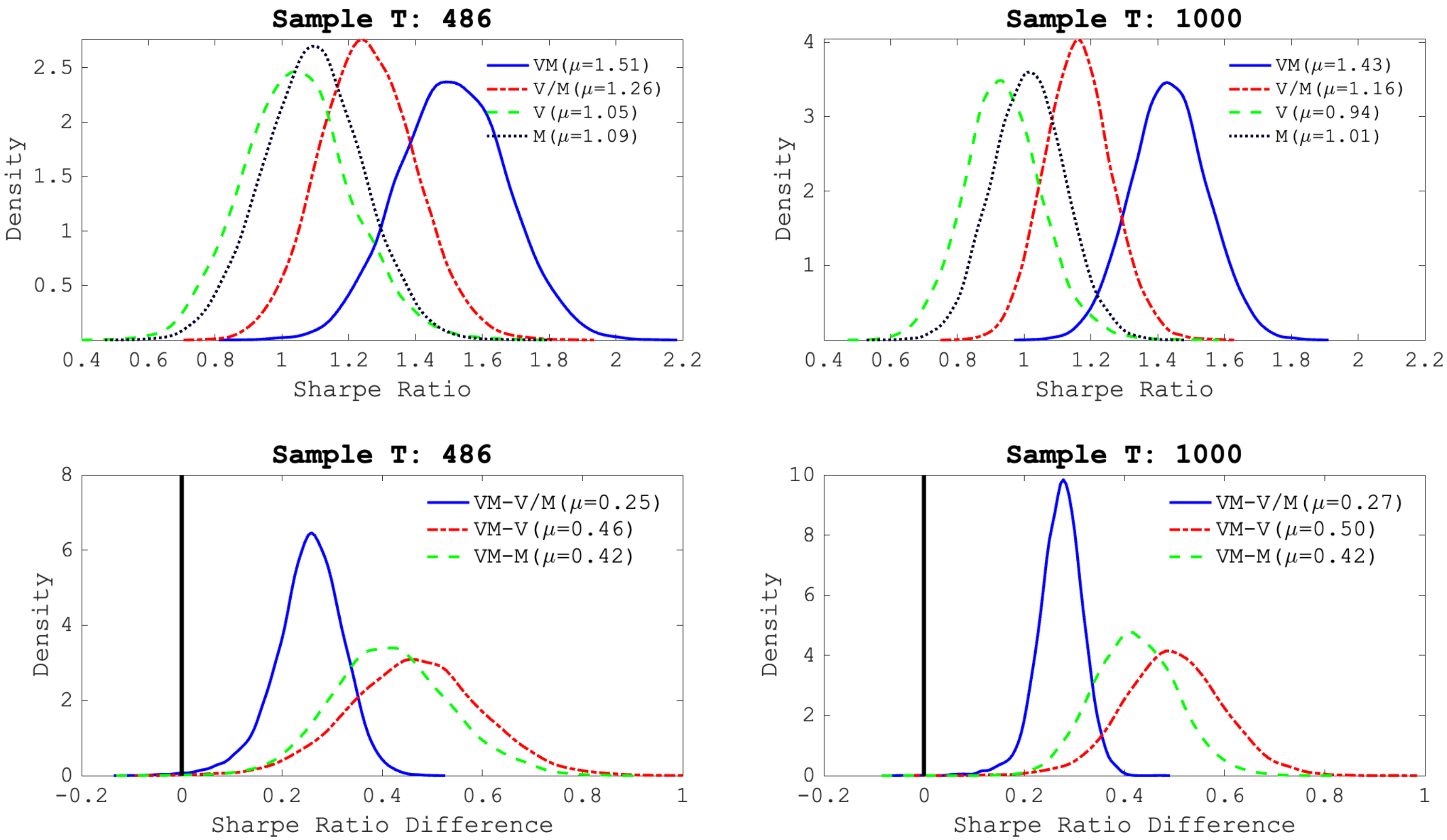

Figure IA.8. Sharpe Ratio Distributions and Spreads. The figure plots, in the upper panels, the empirical distributions of tangency portfolio Sharpe ratios computed over $\Theta = 10{,}000$ Monte Carlo simulations of the 48 value and momentum test asset excess returns. The DGP uses a ten-latent-factor model, extracted from the true test assets using RP-PCA with RP-weight $\omega = 20$. Parameters are calibrated to the first and second moments of the latent factors and loadings, as well as the block-diagonal of the covariance matrix of the residuals. The simulated tangency portfolios are formed from combining nine-latent-factor models using mean–variance weights, where the models are extracted from each of: (i) the full ($N = 48$) joint cross-section of test assets, (ii) the 24 value test assets, and (ii) the 24 momentum test assets, respectively. From these three nine-factor models, we form four tangency portfolios: π_{VM}, π_V, π_M, and the naïve, mean–variance-weighted, combination of π_V and π_M, $\pi_{V/M}$. We repeat this procedure, so as to simulate for $T = \{486, 1000\}$. We compute the maximum Sharpe ratio on each replication, and plot their respective distributions. The lower panels present the difference between π_{VM} and each of the other tangency portfolio Sharpe ratios, respectively. The mean values of each of the distributions are presented in the legend of the corresponding panel.

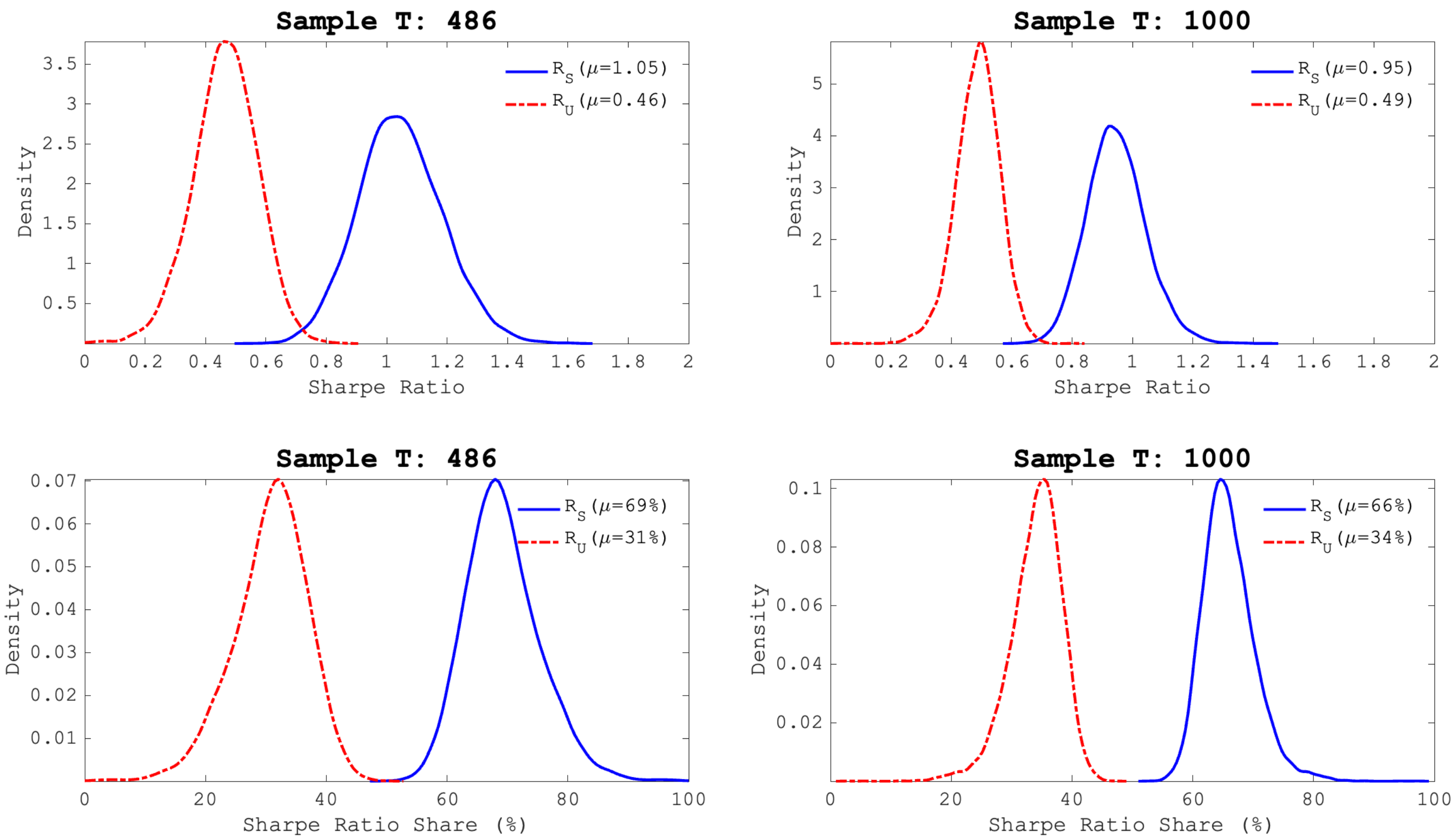

Figure IA.9. Decomposed Sharpe Ratio Distributions. The figure plots, in the upper panels, the empirical distributions of the spanned (R_S) and unspanned (R_U) decomposition components of the optimal nine-latent-factor model tangency portfolio (π_{VM}) Sharpe ratio, computed over Θ = 10,000 Monte Carlo simulations of value and momentum everywhere test asset excess returns. The DGP uses a ten-latent-factor model, extracted from the true test assets using RP-PCA with RP-weight $\omega = 20$. Parameters are calibrated to the first and second moments of the latent factors and loadings, as well as the block-diagonal of the covariance matrix of the residuals. The decomposition segments π_{VM} into (i) a component related to the naïve combination of value and momentum factors ($\pi_{V/M}$), captured by combining two separate value (π_V) and momentum (π_M) tangency portfolios with mean–variance weights, and (ii) a residual component, which captures the marginal gains from extracting a factor structure from the full joint cross-section of test asset excess returns. For further details, refer to Section IV.D, in the main analysis. We repeat this procedure, so as to simulate for $T = \{486, 1000\}$. The lower panels present the distributions of the spanned and unspanned Sharpe ratios as a share of the total Sharpe ratio (π_{VM}), respectively. The mean values of each of the distributions are presented in the legend of the corresponding panel.

IA.5.6 Third-Pass Evidence

Table IA.8 presents outputs of the loadings from Equation (IA.10), the initial time-series spanning regressions of the full range of candidate factor innovations on each of the de-meaned latent factors, η_{F_k}, as well as the explained variation, R^2_{1-k}, for factors F_k for $k = 1, 2, \ldots, 9$.

[Table IA.8 about here.]

Table IA.9 presents the full range of candidate factor risk premia from Equation (IA.11a), given by the latent factor prices of risk multiplied by the candidate factor exposures to the latent factors, and Sharpe ratios for factors F_{1-k} for $k = 1, 2, \ldots, 9$.

[Table IA.9 about here.]

Table IA.10 presents the full range of univariate spanning regressions of each of R_{VM}, R_S, and R_U on the full universe of candidate risk factors. All factors, including the dependent variables, are de-nosied (cleaned) outputs from the third-pass, as per Equation (IA.11b), and are therefore return-based and free from measurement error.

[Table IA.10 about here.]

Figure IA.10 presents correlations between the de-noised decomposition components, R_S and R_U, and the 34 de-noised macro-financial candidate risk factors with significant risk premia at the 5% level using the optimal nine-latent-factor model from the third-pass. Those nine factors identified by the LASSO estimation, in Figure 9, are highlighted in red.

[Figure IA.10 about here.]

Table IA.8

Exposures of Candidate Factors to Latent Factors (Full)

The table presents the risk exposures of the candidate risk factors to the nine latent factors entering the optimal pricing kernel, estimated in the third-pass of the Giglio and Xiu (2021) procedure (Equation (9)). From Panels A to C, the candidate risk factors are grouped as follows: (A) the tangency portfolios and components of Table 5, (B) the *tradable* factors, and (C) the *non-tradable macro-financial* factors. Panel 1 shows the risk exposures, η_{F_k}, whereas Panel 2 reports the explained variation, R^2_{1-k} (in percent), for each F_k for $k = 1, \ldots, 9$. The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ (see Table 1). Tradable factors enter raw being returns, whereas non-tradable factors are expressed as innovations taken as residuals from an AR(1) process. We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987). The sample is monthly from 07/1983–12/2023.

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
Panel A: Decomposition																		
R_{VM}	0.05***	0.06***	0.03***	0.24***	0.05***	0.05***	0.36***	0.59***	0.22***	12.69	15.57	15.92	30.68	31.34	31.82	51.03	92.80	100.00
R_S	0.08***	0.08***	0.04***	0.15***	0.04***	0.02***	0.30***	0.26***	−0.07***	40.54	48.22	49.39	58.45	59.29	59.40	80.13	92.86	93.83
R_U	−0.02***	−0.02***	−0.01	0.09***	0.01	0.03***	0.06***	0.32***	0.29***	7.58	8.18	8.09	13.71	13.57	13.93	15.17	52.39	88.07
R_V	0.06***	0.04***	0.01**	−0.06***	0.04***	−0.01	0.33***	0.21***	−0.01	30.23	33.82	33.98	36.21	37.19	37.13	72.27	84.20	84.22
R_M	0.05***	0.06***	0.04***	0.27***	0.02***	0.04***	0.09***	0.15***	−0.08***	26.44	33.85	35.53	80.45	80.71	81.72	84.34	90.54	92.67
Panel B: Tradable																		
jkpmom	−0.11***	0.02	0.03	1.00***	−0.17***	0.08	−0.21***	−0.21***	0.37***	11.18	11.17	11.11	61.49	62.73	62.85	63.82	64.74	68.12
jkpval	−0.01	0.01	−0.16***	−0.83***	0.02	−0.08	0.17***	1.03***	−0.06	0.04	−0.18	2.71	37.59	37.51	37.56	38.12	61.55	61.55
jkplorsk	−0.23***	0.02	0.01	0.08	−0.31***	0.14*	0.17**	0.58***	0.07	42.63	42.57	42.47	42.71	47.46	48.26	48.89	56.25	56.28
jkpprofg	−0.05**	0.07*	0.08**	0.70***	−0.18***	0.03	−0.04	−0.26**	0.01	2.00	2.68	3.43	28.20	29.88	29.75	29.64	30.95	30.80
jkpqual	−0.10***	0.11***	0.11***	0.44***	−0.27***	0.13	−0.21**	−0.18*	0.11	8.52	10.38	11.74	21.82	25.42	25.92	26.85	27.40	27.53
jkpsize	0.00	−0.13***	−0.21***	−0.47***	0.13*	0.07	−0.04	0.43***	−0.20**	0.00	2.57	7.81	18.71	19.53	19.58	19.46	23.42	24.29
jkpinv	−0.06***	−0.16***	−0.05	−0.32***	−0.01	0.03	0.13	0.64***	0.12	3.46	7.36	7.51	12.55	12.35	12.21	12.44	21.36	21.56
fxcar	0.12***	0.16***	−0.13***	−0.09	0.09	0.10	0.01	0.10	0.07	12.07	16.33	17.79	17.98	18.27	18.50	18.32	18.35	18.29
comcar	0.03*	0.01	0.01	0.21***	0.11	−0.12*	−0.39***	0.47***	−0.52***	0.88	0.67	0.49	2.19	2.38	2.80	6.45	10.94	17.76
jkplolev	0.03	0.11***	0.08**	0.26**	0.06	0.10	−0.27**	−0.67***	−0.04	0.71	2.48	3.07	6.36	6.31	6.42	7.98	17.62	17.48
eqstrad	−0.11***	−0.05	−0.02	−0.04	−0.28***	0.09	0.12	−0.19	−0.07	10.29	10.19	9.94	9.76	13.00	13.10	13.05	13.50	13.37
jkpprof	−0.06***	0.19***	0.12***	0.09	−0.21***	0.03	−0.09	0.08	0.05	3.22	9.03	10.62	10.84	13.04	12.88	12.88	12.83	12.70
irstrad	−0.12***	−0.01	0.03	0.00	−0.03	0.04	0.20*	−0.03	−0.19*	11.28	11.06	10.90	10.65	10.49	10.39	10.85	10.60	11.21
bab	0.07***	−0.15***	−0.08	0.14*	−0.25***	0.04	−0.05	0.06	0.26**	3.17	6.11	6.44	7.33	10.06	9.91	9.75	9.61	11.08
bdstrad	−0.11***	−0.08	−0.04	0.02	−0.10	0.02	0.02	−0.29**	−0.14	9.12	9.53	9.41	9.19	9.58	9.35	9.11	10.47	10.69
jkpseas	−0.10***	−0.08	−0.08	0.11*	−0.09	0.01	−0.14	0.11	0.17	7.95	8.64	9.15	9.54	9.72	9.53	9.83	9.87	10.36
jkpstrmv	0.03	−0.04	0.03	−0.24*	−0.06	0.18	0.21	0.40**	−0.02	0.73	0.85	0.73	3.60	3.55	4.80	5.74	9.05	8.86
fxstrad	−0.08***	−0.09	0.01	0.14**	−0.22*	0.01	0.06	−0.09	−0.10	6.62	6.99	6.75	7.64	9.44	9.20	8.98	8.85	8.82
comstrad	−0.06**	−0.13**	−0.07	0.21***	−0.12	0.02	−0.10	−0.22*	−0.06	3.54	5.06	5.23	7.65	8.07	7.81	7.91	8.63	8.46
ficar	0.03	0.06	−0.05	0.15**	−0.03	−0.22***	0.27**	0.10	−0.18**	0.43	0.80	0.97	1.84	1.67	3.56	5.18	5.18	5.84
vrp	0.03	0.06	−0.21**	−0.03	0.12	0.03	−0.06	0.14	0.02	0.82	1.17	5.83	5.62	6.19	5.97	5.79	5.95	5.72
jkpacc	−0.01	−0.03	0.01	−0.14*	−0.12*	0.08	−0.02	0.28**	0.27**	0.17	0.08	−0.10	0.63	1.04	1.09	0.88	2.36	4.03
jkpdebiss	−0.03*	−0.10**	0.00	0.11	−0.04	0.13	−0.22**	−0.15	−0.06	0.83	2.22	2.00	2.43	2.31	2.69	3.73	4.02	3.88
eqcar	−0.03	−0.09	−0.09*	−0.07	0.00	−0.01	0.19	−0.13	−0.21**	0.38	1.40	2.09	2.20	1.95	1.71	2.19	2.27	3.10

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Table IA.8 — Continued

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
Panel C: Non-tradable Macro-Financial																		
Panel C1: Financial Uncertainty																		
gfc	0.33***	0.12***	−0.16***	−0.15***	0.13***	0.11***	−0.10***	0.08*	−0.05	79.11	81.36	83.86	84.98	85.94	86.47	86.68	86.79	86.82
vix/vxo	−0.22***	−0.13***	−0.04	0.01	−0.22***	−0.03	−0.11	0.00	0.06	40.77	43.38	43.38	43.27	45.79	45.72	45.91	45.79	45.78
impvar	−0.21***	−0.08**	−0.01	0.04	−0.18*	−0.01	−0.34***	−0.13	0.09	40.18	40.38	40.20	40.19	41.02	40.97	43.50	43.81	43.83
avgcor	−0.13***	−0.09***	−0.06	−0.09	−0.17***	0.00	0.12	−0.22**	−0.12	14.09	15.26	15.46	15.69	17.24	17.07	17.29	18.20	18.38
corp	−0.12***	−0.08**	0.16**	0.01	−0.14*	−0.05	0.13	0.06	−0.02	11.47	12.35	15.20	15.02	15.95	15.84	16.11	16.01	15.83
finunc	−0.12***	−0.06**	0.06	0.12*	−0.19***	−0.10	−0.02	−0.12	−0.02	12.16	12.60	12.80	13.28	15.23	15.51	15.34	15.46	15.29
emvfincri	−0.10**	−0.04	0.06	0.00	−0.13*	0.05	0.04	−0.18*	−0.21**	8.56	8.62	8.90	8.71	9.49	9.38	9.23	9.75	10.70
move	−0.12***	−0.03	−0.07*	−0.10	−0.02	−0.06	−0.13	−0.12	−0.01	10.28	10.21	10.55	10.82	10.64	10.58	10.80	10.89	10.69
geqrv	−0.12***	−0.04	0.03	−0.01	−0.01	−0.09	−0.03	0.03	0.05	10.33	10.41	10.30	10.10	9.91	10.04	9.86	9.68	9.54
ted	−0.09***	−0.08**	−0.07	−0.14**	−0.05	−0.15	0.02	−0.12	−0.05	6.67	7.60	7.89	8.73	8.65	9.42	9.21	9.33	9.17
mf2	0.09***	−0.01	−0.15***	−0.01	0.06	−0.01	0.09	0.03	0.04	5.76	5.60	8.05	7.87	7.92	7.73	7.74	7.56	7.40
fsi	−0.10***	0.02	0.00	−0.02	−0.14**	−0.11*	−0.02	−0.05	0.02	7.19	7.01	6.79	6.56	7.64	8.02	7.80	7.62	7.39
perunc	0.01	−0.11*	0.00	0.00	0.01	−0.16	−0.30	0.51***	0.06	0.30	1.01	0.44	−0.13	−0.75	−0.56	1.50	6.39	5.88
mf3	−0.04*	0.08***	0.18***	−0.04	−0.06	0.10	0.07	−0.04	0.04	1.04	1.76	5.18	5.05	5.04	5.24	5.17	5.00	4.84
mf1	−0.05*	−0.04	0.07	0.00	−0.09	0.06	0.08	−0.05	−0.25*	1.70	1.71	2.00	1.80	2.04	1.99	1.98	1.82	3.22
shtint	0.04	0.07*	−0.04	0.04	−0.03	−0.02	0.06	−0.04	−0.23**	1.09	1.64	1.59	1.46	1.32	1.14	1.02	0.85	2.00
Panel C2: Liquidity																		
icap	0.24***	0.18***	0.12***	−0.31***	0.28***	0.19***	0.09	0.02	−0.14**	45.55	50.33	51.81	56.36	61.07	62.45	62.57	62.50	62.94
noise	−0.10***	−0.05	0.10	0.06	−0.12	−0.11	0.13	−0.10	0.06	8.27	8.37	9.37	9.31	9.79	10.00	10.28	10.29	10.18
psliq	0.09***	0.05	0.06	0.08	0.12**	0.08	−0.24*	0.02	0.22**	6.69	6.85	7.08	7.18	7.81	7.89	9.24	9.06	10.12
Panel C3: Crash Risk																		
adbear	−0.26***	−0.13***	−0.13***	−0.03	−0.23***	−0.15	−0.09	−0.12	−0.02	57.40	58.22	60.10	59.98	62.30	62.79	62.92	63.08	62.92
skew	0.07***	0.06**	0.12**	0.06	0.02	0.09	0.01	0.21**	−0.04	3.64	4.04	5.57	5.54	5.38	5.54	5.34	6.08	5.93
tail	0.03	0.07**	0.01	0.14*	−0.08	0.00	0.00	0.00	−0.03	0.53	1.12	0.93	1.63	1.76	1.56	1.35	1.15	0.96

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Table IA.8 — Continued

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
Panel C4: Macro																		
ygap	−0.15***	−0.10***	−0.21***	0.03	−0.08**	−0.10	−0.45***	0.03	0.12	17.74	19.25	24.12	24.00	24.25	24.47	29.69	29.56	29.79
emvov	−0.14***	−0.06	−0.06	−0.04	−0.18***	−0.03	0.19*	−0.11	−0.18*	15.76	16.27	16.46	16.35	18.08	17.95	18.69	18.80	19.47
emvout	−0.13***	−0.06*	−0.07	−0.04	−0.17***	−0.03	0.19*	−0.11	−0.22**	14.33	14.85	15.17	15.05	16.65	16.50	17.18	17.28	18.33
emvinf	−0.12***	−0.07*	−0.15**	−0.02	−0.13***	0.00	0.15*	−0.03	−0.14	10.87	11.44	13.81	13.64	14.45	14.26	14.65	14.49	14.84
macunc	−0.10***	−0.01	0.15**	0.02	−0.14	−0.03	0.00	−0.07	−0.06	7.84	7.68	9.99	9.83	10.80	10.65	10.47	10.38	10.29
realunc	−0.07**	−0.03	0.12*	0.01	−0.15	−0.01	−0.03	−0.14	−0.03	4.42	4.37	5.79	5.60	6.82	6.63	6.46	6.71	6.55
emvfx	−0.07***	−0.02	−0.04	0.08	−0.14**	0.06	0.20*	−0.05	−0.06	3.60	3.44	3.43	3.54	4.53	4.47	5.28	5.13	5.02
ui	0.02	−0.06*	−0.15***	0.06	0.09*	−0.02	−0.18*	0.06	−0.02	0.32	0.75	2.75	2.73	2.95	2.73	3.38	3.21	2.99
ogap	−0.01	0.03	−0.12	0.05	0.05	−0.07	−0.16*	−0.05	0.18	0.08	0.03	1.35	1.25	1.22	1.23	1.71	1.55	2.20
mp	0.05**	−0.03	−0.06	0.03	0.09	−0.04	0.04	−0.14	−0.12	1.90	1.82	1.94	1.74	2.01	1.87	1.67	1.86	1.97
dei	−0.02	0.03	−0.04	−0.03	0.03	0.12*	−0.07	−0.19*	−0.11	0.34	0.21	0.19	0.03	−0.15	0.22	0.11	0.63	0.73
Panel C5: Interest Rate & Monetary Policy																		
ltychg	0.00	0.02	−0.19***	−0.31***	0.26***	−0.21***	−0.62***	−0.38***	0.09	0.00	−0.15	3.69	8.19	12.05	13.65	23.66	26.65	26.71
emvmon	−0.14***	−0.04	−0.05	−0.06	−0.15***	−0.01	0.23**	−0.16*	−0.26***	16.50	16.55	16.64	16.67	17.88	17.71	18.82	19.23	20.80
emvir	−0.13***	−0.07*	−0.11**	−0.09	−0.13**	−0.06	0.17	−0.10	−0.12	13.36	14.03	15.20	15.44	16.18	16.15	16.73	16.76	16.93
upr	−0.07*	−0.02	0.22***	−0.03	−0.18**	−0.06	0.30**	0.23**	0.08	3.75	3.56	8.25	8.08	9.87	9.80	12.12	13.06	13.02
trms	−0.02	−0.03	−0.10*	−0.28***	0.10	−0.22***	−0.29***	−0.22**	−0.04	0.28	0.20	1.16	4.74	5.15	6.96	8.98	9.81	9.66
mpjksporg	0.10***	0.01	−0.01	−0.12	0.18**	−0.03	0.07	−0.10	−0.21**	8.08	7.79	7.55	8.23	9.41	9.14	8.94	8.86	9.63
mpmarinf	0.02	0.02	−0.22***	0.08	0.13	0.13	−0.40**	−0.04	0.14	0.45	0.16	4.79	5.06	6.09	5.99	9.47	9.23	9.41
uts	0.00	−0.01	−0.17***	−0.19***	0.21***	−0.01	−0.26***	−0.23*	0.18*	0.00	−0.21	2.38	3.61	6.23	6.01	7.79	8.66	9.32
mpbsortfit	0.04	0.05	−0.14**	0.02	0.17**	−0.06	−0.37**	−0.17*	0.22**	1.36	1.69	3.36	3.18	4.40	4.35	7.54	7.89	8.80
mpbsort	−0.10***	−0.02	0.03	−0.01	−0.02	−0.14	−0.08	−0.10	0.07	7.14	6.91	6.76	6.52	6.29	6.73	6.65	6.61	6.47
mpjkff4	−0.06***	0.01	−0.06	0.02	−0.05	−0.19	−0.35*	−0.08	0.22	1.61	1.42	1.31	1.13	0.87	2.22	4.90	4.76	5.66
mjlsapu4	0.05***	−0.03	0.07	−0.13	0.15**	−0.20**	−0.07	−0.23**	−0.09	2.48	2.35	2.57	3.39	3.93	4.68	4.58	5.46	5.41
mpbs	−0.07***	0.00	−0.04	0.01	0.04	−0.16	−0.28*	−0.14	0.14	2.38	2.13	1.98	1.75	1.57	2.30	4.03	4.17	4.37
mpmar	−0.06**	0.03	0.02	−0.03	−0.02	−0.24*	−0.21	−0.05	0.16	1.83	1.99	1.77	1.50	1.22	2.75	3.50	3.27	3.58
mjsummp	−0.03*	0.01	0.00	−0.09	0.11	−0.23*	−0.20	−0.19*	0.09	0.45	0.29	0.03	0.26	0.54	1.90	2.57	3.17	3.13
mjdelphu3	−0.01	0.04	−0.05	0.09	−0.04	0.20**	−0.29	0.09	0.16	0.15	0.04	0.12	0.52	0.26	0.53	2.09	2.00	2.33
mjodysu2	−0.06***	0.06	0.02	−0.04	0.02	−0.04	−0.17	−0.07	0.03	2.28	2.58	2.36	2.19	1.97	1.83	2.30	2.17	1.93
mjratesu1	−0.04*	−0.01	−0.09	0.05	0.02	−0.14	−0.08	0.01	0.22	1.03	0.78	1.27	1.12	0.91	1.29	1.15	0.90	1.79
mpjkcbi	0.02	0.01	−0.02	−0.02	0.01	−0.01	0.33**	−0.06	0.06	0.27	0.07	−0.13	−0.34	−0.56	−0.78	1.56	1.40	1.25
mpjkspnew	0.02	−0.04	0.03	0.07	−0.05	0.08	0.19*	−0.15	0.10	0.21	0.22	0.09	0.09	−0.03	0.06	0.70	0.95	0.93
mpjkmed	−0.02	0.06	0.00	−0.06	0.01	−0.07	−0.08	0.19	−0.11	0.46	0.69	0.45	0.39	0.16	0.12	0.02	0.57	0.61
mpjkpm	−0.03*	0.05	0.02	−0.03	−0.03	−0.04	−0.06	0.19	−0.09	0.76	0.82	0.64	0.44	0.26	0.13	−0.02	0.55	0.50
mpjkpc	−0.02	0.05	0.02	−0.04	−0.03	−0.04	0.04	0.19	−0.09	0.50	0.68	0.48	0.31	0.13	−0.06	−0.24	0.33	0.31
mpjkcbimed	−0.01	−0.01	0.03	0.04	−0.08	0.04	0.22**	0.01	0.04	0.12	−0.10	−0.22	−0.38	−0.31	−0.42	0.55	0.31	0.11

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Table IA.8 — Continued

	Panel 1: Risk Exposures									Panel 2: Explained Variation								
	η_{F_1}	η_{F_2}	η_{F_3}	η_{F_4}	η_{F_5}	η_{F_6}	η_{F_7}	η_{F_8}	η_{F_9}	$R^2_{F_{1-1}}$	$R^2_{F_{1-2}}$	$R^2_{F_{1-3}}$	$R^2_{F_{1-4}}$	$R^2_{F_{1-5}}$	$R^2_{F_{1-6}}$	$R^2_{F_{1-7}}$	$R^2_{F_{1-8}}$	$R^2_{F_{1-9}}$
Panel C6: Political Uncertainty																		
emvpol	−0.14***	−0.04	−0.07	−0.03	−0.18***	−0.06	0.24**	−0.11	−0.21**	14.66	14.80	15.18	15.04	16.66	16.62	17.95	18.03	18.97
epu	−0.10***	−0.04	−0.01	0.06	−0.18**	0.12*	0.30***	−0.10	−0.22**	8.05	8.16	7.97	7.95	9.65	10.09	12.21	12.23	13.30
emvfisc	−0.11***	−0.07	−0.05	0.01	−0.13**	−0.05	0.20**	−0.04	−0.10	9.73	10.24	10.32	10.13	10.98	10.88	11.70	11.55	11.64
emvtrad	−0.08*	−0.09	−0.18**	−0.01	−0.12*	−0.06	0.18	−0.10	−0.02	4.93	5.93	9.38	9.19	9.82	9.77	10.40	10.44	10.25
gepu	−0.09***	0.04	−0.01	0.13*	−0.05	−0.03	0.39***	−0.28**	−0.22*	4.58	4.42	4.13	4.71	4.95	4.79	7.03	8.06	8.88
gepuppp	−0.08***	0.05	−0.01	0.12	−0.05	−0.04	0.40***	−0.26**	−0.18	3.72	3.61	3.31	3.76	3.99	3.82	6.34	7.26	7.75
gpr(thrts)	−0.03	−0.02	−0.07	0.05	−0.06	0.11	0.08	−0.07	0.02	0.92	0.78	1.09	1.02	1.02	1.35	1.30	1.18	0.98
gpr	−0.03	−0.05*	−0.02	0.05	−0.10	0.05	0.02	−0.05	0.02	0.75	0.99	0.80	0.70	1.13	1.01	0.80	0.63	0.42
gpr(acts)	−0.02	−0.06**	0.03	0.01	−0.12	−0.02	−0.03	−0.03	0.01	0.38	0.77	0.68	0.48	1.10	0.90	0.70	0.50	0.29
Panel C7: Behavioral																		
dtoat	0.28***	0.20***	0.18***	−0.05	0.27***	0.24***	0.24***	−0.06	−0.15***	60.45	66.83	70.50	70.58	74.97	77.38	78.90	78.93	79.48
dtoy	0.27***	0.19***	0.15***	−0.03	0.25***	0.18***	0.25***	−0.08	−0.09*	59.55	65.29	67.75	67.74	71.43	72.67	74.31	74.40	74.57
disag	0.08***	0.02	−0.01	0.16**	−0.01	0.08	0.22**	−0.25***	−0.01	4.61	4.50	4.31	5.29	5.10	5.14	6.19	7.33	7.14
sent	−0.02	0.03	−0.04	−0.02	0.03	−0.21***	0.01	0.10	0.21**	0.37	0.30	0.29	0.09	−0.05	1.59	1.39	1.40	2.41

Table IA.9
Risk Premia of Candidate Factors (Full)

The table presents the risk premium estimates obtained with the three-pass method of Giglio and Xiu (2021) (Equation (10a)). From Panels A to C, the candidate risk factors are grouped as follows: (A) the tangency portfolios and components of Table 5, (B) the *tradable* factors, and (C) the *non-tradable macro-financial* factors. Panel 1 shows the risk premium estimates (λ), whereas Panel 2 reports the Sharpe ratio of the de-noised candidate risk factor. We report the estimates using models including an increasing number of latent factors, F_{1-k} for $k = 1, 2, \ldots, 9$. The latent factors are obtained by applying RP-PCA with RP-weight $\omega = 20$ (see Table 1). Tradable factors are returns and therefore enter raw, whereas non-tradable factors are expressed as innovations taken as residuals from an AR(1) process. We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * denote statistical significance at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated as in Giglio and Xiu (2021). The sample is monthly from 07/1983–12/2023.

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$SR_{F_{1-1}}$	$SR_{F_{1-2}}$	$SR_{F_{1-3}}$	$SR_{F_{1-4}}$	$SR_{F_{1-5}}$	$SR_{F_{1-6}}$	$SR_{F_{1-7}}$	$SR_{F_{1-8}}$	$SR_{F_{1-9}}$
Panel A: Decomposition																		
R_{VM}	2.29***	2.84***	2.93***	5.61***	5.75***	5.86***	9.31***	16.75***	18.03***	0.52	0.58	0.59	0.82	0.83	0.84	1.06	1.42	1.47
R_S	3.32***	4.03***	4.15***	5.85***	5.98***	6.03***	8.93***	12.26***	11.88***	0.52	0.58	0.59	0.77	0.78	0.78	1.00	1.28	1.23
R_U	−1.03**	−1.20***	−1.22***	−0.25	−0.23	−0.17	0.38	4.48***	6.15***	0.52	0.58	0.59	0.09	0.08	0.06	0.13	0.86	0.91
R_V	2.38***	2.78***	2.83***	2.12**	2.23**	2.21**	5.34***	8.01***	7.95***	0.52	0.58	0.59	0.42	0.44	0.44	0.76	1.06	1.05
R_M	2.20***	2.77***	2.89***	5.98***	6.04***	6.13***	6.98***	8.89***	8.43***	0.52	0.58	0.59	0.82	0.82	0.83	0.93	1.15	1.07
Panel B: Tradable																		
bdstrad	−4.57**	−5.13**	−5.31**	−5.03**	−5.29**	−5.20**	−5.41**	−8.99***	−9.85***	0.52	0.58	0.59	0.56	0.57	0.56	0.59	0.88	0.93
jkpdebiss	−1.36*	−2.28**	−2.28**	−0.99	−1.10	−0.83	−3.00	−4.94*	−5.25**	0.52	0.51	0.51	0.20	0.22	0.15	0.47	0.73	0.77
ficar	1.00	1.57	1.38	3.09*	3.00*	2.45	5.08**	6.32**	5.42*	0.52	0.54	0.40	0.68	0.65	0.40	0.70	0.85	0.68
eqstrad	−4.85***	−5.12***	−5.13***	−5.56***	−6.17***	−5.86***	−5.01**	−7.36**	−7.79**	0.52	0.56	0.56	0.60	0.57	0.53	0.46	0.65	0.68
comstrad	−2.84**	−3.77**	−4.09**	−1.50	−1.77	−1.75	−2.92	−5.71**	−6.08**	0.52	0.56	0.57	0.18	0.20	0.20	0.33	0.61	0.64
eqcar	−0.96	−1.83	−2.20*	−3.20**	−3.21**	−3.18**	−1.46	−3.02	−4.12*	0.52	0.49	0.46	0.62	0.62	0.62	0.25	0.50	0.61
fxcar	5.29***	6.85***	6.46***	5.46**	5.70**	5.94***	6.05**	7.27***	7.61***	0.52	0.58	0.52	0.44	0.45	0.47	0.47	0.57	0.59
jkpstrmv	1.28	0.86	0.95	−1.88	−2.04	−1.61	0.46	5.59**	5.50*	0.52	0.29	0.31	0.32	0.34	0.23	0.06	0.60	0.59
fxstrad	−3.89***	−4.44***	−4.36***	−2.67	−3.13	−3.07	−2.70	−3.70	−4.30	0.52	0.58	0.57	0.33	0.34	0.34	0.30	0.40	0.46
irstrad	−5.08***	−5.21***	−5.07***	−5.16***	−5.26***	−5.05**	−3.41	−3.58	−4.74*	0.52	0.54	0.53	0.54	0.55	0.53	0.34	0.36	0.44
jkplolev	1.26	2.28**	2.54**	5.56**	5.72**	5.91**	3.34	−5.24	−5.46	0.52	0.49	0.48	0.74	0.75	0.76	0.38	0.42	0.44
bab	2.68*	1.39	1.18	2.89	2.26	2.37	1.94	2.68	4.18*	0.52	0.19	0.15	0.35	0.22	0.23	0.19	0.26	0.38
jkpacc	−0.61	−0.88	−0.82	−2.39	−2.70	−2.52	−2.69	0.87	2.40	0.52	0.56	0.49	0.74	0.67	0.59	0.62	0.15	0.34
jkpseas	−4.23**	−4.91***	−5.15***	−3.91*	−4.15*	−4.13*	−5.50**	−4.15	−3.23	0.52	0.58	0.59	0.43	0.45	0.45	0.58	0.43	0.33
vrp	1.37	1.96	1.08	0.77	1.08	1.13	0.63	2.40	2.54	0.52	0.56	0.15	0.11	0.14	0.15	0.08	0.31	0.32
comcar	1.43*	1.50*	1.56*	3.83***	4.05***	3.77***	−0.02	5.69**	3.00	0.52	0.55	0.56	0.79	0.78	0.67	0.00	0.56	0.23
jkpsize	−0.02	−1.23	−1.91	−7.28**	−6.88**	−6.72**	−7.18**	−1.61	−2.75	0.52	0.26	0.23	0.58	0.54	0.52	0.56	0.12	0.19
jkpval	−0.30	−0.25	−0.76	−10.31***	−10.22***	−10.37***	−8.76**	4.51	4.20	0.52	0.42	0.15	0.59	0.58	0.59	0.49	0.20	0.19
jkpmom	−5.03**	−4.72**	−4.62**	6.99*	6.55	6.71	4.74	1.98	4.15	0.52	0.49	0.47	0.31	0.29	0.30	0.21	0.09	0.18
jkpprofg	−2.12	−1.43	−1.15	6.91**	6.38**	6.44**	6.03*	2.71	2.77	0.52	0.29	0.20	0.46	0.41	0.41	0.39	0.17	0.17
jkpinv	−2.79**	−4.26***	−4.43***	−8.12***	−8.12***	−8.04***	−6.77***	1.48	2.16	0.52	0.54	0.55	0.79	0.79	0.78	0.65	0.11	0.16
jkpqual	−4.37**	−3.33	−2.97	2.20	1.43	1.71	−0.31	−2.62	−2.01	0.52	0.36	0.30	0.16	0.10	0.12	0.02	0.17	0.13
jkpprof	−2.69*	−0.91	−0.52	0.53	−0.08	−0.02	−0.87	0.18	0.47	0.52	0.10	0.05	0.05	0.01	0.00	0.08	0.02	0.04
jkplorsk	−9.78***	−9.59***	−9.54***	−8.57**	−9.44**	−9.11**	−7.44*	0.04	0.42	0.52	0.51	0.51	0.46	0.48	0.46	0.37	0.00	0.02

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Table IA.9 — Continued

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$SR_{F_{1-1}}$	$SR_{F_{1-2}}$	$SR_{F_{1-3}}$	$SR_{F_{1-4}}$	$SR_{F_{1-5}}$	$SR_{F_{1-6}}$	$SR_{F_{1-7}}$	$SR_{F_{1-8}}$	$SR_{F_{1-9}}$
Panel C: Non-tradable Macro-Financial																		
Panel C1: Financial Uncertainty																		
move	−4.90***	−5.19***	−5.47***	−6.63***	−6.70***	−6.88***	−8.15***	−9.69***	−9.76***	0.52	0.55	0.56	0.66	0.67	0.68	0.79	0.92	0.92
ted	−3.92**	−4.68***	−4.89***	−6.54***	−6.68***	−7.05***	−6.93***	−8.46***	−8.71***	0.52	0.58	0.59	0.74	0.75	0.75	0.74	0.89	0.92
avgcor	−5.68***	−6.54***	−6.73***	−7.77***	−8.27***	−8.27***	−7.10***	−9.92***	−10.58***	0.52	0.58	0.59	0.67	0.68	0.68	0.57	0.78	0.82
emvfincri	−4.40**	−4.77**	−4.57**	−4.59**	−4.97**	−4.85**	−4.47	−6.77*	−7.95**	0.52	0.56	0.52	0.52	0.54	0.53	0.48	0.71	0.79
impvar	−9.38***	−9.79***	−9.78***	−9.11**	−9.39**	−9.60**	−12.79***	−14.75***	−14.17***	0.52	0.55	0.55	0.51	0.54	0.54	0.71	0.80	0.77
fsi	−4.11***	−3.93**	−3.95**	−4.13**	−4.53**	−4.88**	−5.11**	−5.70**	−5.62**	0.52	0.50	0.50	0.53	0.53	0.55	0.57	0.64	0.63
vix/vxo	−9.57***	−10.77***	−10.87***	−10.70***	−11.34***	−11.42***	−12.50***	−12.44***	−12.08***	0.52	0.57	0.58	0.57	0.59	0.59	0.64	0.64	0.62
finunc	−5.28***	−5.87***	−5.68***	−4.35**	−4.91**	−5.13**	−5.28**	−6.75***	−6.85***	0.52	0.57	0.54	0.41	0.43	0.44	0.45	0.57	0.58
mf1	−1.97	−2.31	−2.10	−2.16	−2.41	−2.28	−1.46	−2.06	−3.49	0.52	0.58	0.47	0.48	0.49	0.46	0.28	0.40	0.55
geqrv	−4.89***	−5.28***	−5.19***	−5.29**	−5.33**	−5.55**	−5.84**	−5.43*	−5.20	0.52	0.56	0.55	0.56	0.56	0.57	0.60	0.56	0.53
mf2	3.63**	3.51**	3.02*	2.91*	3.09*	3.07*	3.90*	4.24*	4.45*	0.52	0.51	0.36	0.35	0.36	0.36	0.45	0.49	0.52
gfc	13.86***	15.01***	14.63***	12.88***	13.22***	13.54***	12.57***	13.57***	13.33***	0.52	0.56	0.53	0.46	0.47	0.48	0.45	0.48	0.48
perunc	0.87	0.01	0.12	0.49	0.55	−0.09	−2.95	2.71	3.12	0.52	0.00	0.03	0.13	0.15	0.02	0.46	0.28	0.32
corp	−5.08**	−5.83***	−5.33**	−5.19**	−5.60**	−5.70**	−4.40	−3.59	−3.69	0.52	0.58	0.47	0.46	0.48	0.49	0.37	0.30	0.31
shtint	1.58	2.22*	2.10*	2.55*	2.45*	2.40	2.96*	2.44	1.13	0.52	0.57	0.51	0.61	0.58	0.57	0.68	0.56	0.21
mf3	−1.54	−0.83	−0.25	−0.64	−0.81	−0.60	0.06	−0.43	−0.20	0.52	0.20	0.04	0.09	0.12	0.08	0.01	0.06	0.03
Panel C2: Liquidity																		
psliq	3.92***	4.36***	4.56***	5.43***	5.78***	5.95***	3.66*	3.88	5.14*	0.52	0.57	0.58	0.68	0.68	0.69	0.39	0.42	0.52
icap	10.22***	11.86***	12.24***	8.72**	9.55**	9.96**	10.78***	11.06***	10.25**	0.52	0.58	0.59	0.40	0.42	0.43	0.47	0.48	0.44
noise	−4.33**	−4.73**	−4.40**	−3.78**	−4.08**	−4.32**	−2.99	−4.31*	−3.94	0.52	0.56	0.49	0.42	0.44	0.46	0.31	0.44	0.40
Panel C3: Crash Risk																		
skew	2.89*	3.46**	3.87**	4.53**	4.60**	4.80**	4.86**	7.49***	7.26***	0.52	0.58	0.55	0.63	0.64	0.65	0.66	0.95	0.92
adbear	−11.24**	−11.83**	−12.52**	−12.86**	−13.13**	−13.86**	−14.99**	−16.46***	−16.57***	0.52	0.56	0.57	0.58	0.60	0.61	0.66	0.72	0.72
tail	1.10	1.76**	1.79**	3.35***	3.13**	3.14**	3.09*	3.06	2.90	0.52	0.53	0.54	0.77	0.67	0.68	0.67	0.66	0.62

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Table IA.9 — Continued

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$SR_{F_{1-1}}$	$SR_{F_{1-2}}$	$SR_{F_{1-3}}$	$SR_{F_{1-4}}$	$SR_{F_{1-5}}$	$SR_{F_{1-6}}$	$SR_{F_{1-7}}$	$SR_{F_{1-8}}$	$SR_{F_{1-9}}$
Panel C4: Macro																		
dei	−0.91	−0.67	−0.78	−1.23	−1.14	−0.80	−1.53	−3.82*	−4.40**	0.52	0.35	0.34	0.50	0.45	0.24	0.44	0.90	0.97
ygap	−6.38***	−7.34***	−8.02***	−7.72***	−7.96***	−8.17***	−12.45***	−12.06***	−11.37***	0.52	0.58	0.56	0.54	0.55	0.56	0.78	0.75	0.71
realunc	−3.18**	−3.47*	−3.08*	−2.95*	−3.40*	−3.43*	−3.68	−5.50	−5.69	0.52	0.56	0.43	0.41	0.43	0.43	0.46	0.67	0.69
emvout	−5.70***	−6.30***	−6.51***	−6.92***	−7.43***	−7.50***	−5.73**	−7.16***	−8.39***	0.52	0.57	0.58	0.61	0.62	0.63	0.47	0.58	0.66
emvov	−5.98***	−6.58***	−6.76***	−7.19***	−7.72***	−7.80***	−5.97**	−7.43***	−8.45***	0.52	0.57	0.58	0.61	0.62	0.63	0.47	0.58	0.64
emvinf	−4.96***	−5.59***	−6.07***	−6.28***	−6.66***	−6.67***	−5.22**	−5.60**	−6.41***	0.52	0.57	0.56	0.58	0.60	0.60	0.46	0.49	0.55
macunc	−4.24**	−4.37**	−3.89**	−3.63**	−4.04**	−4.10**	−4.11*	−4.98	−5.33	0.52	0.54	0.42	0.39	0.41	0.42	0.42	0.50	0.54
emvfx	−2.85**	−3.02**	−3.15**	−2.24	−2.66	−2.51	−0.58	−1.19	−1.54	0.52	0.55	0.56	0.38	0.40	0.38	0.08	0.16	0.21
ogap	−0.44	−0.15	−0.53	−0.01	0.15	−0.01	−1.53	−2.14	−1.10	0.52	0.11	0.14	0.00	0.04	0.00	0.31	0.43	0.20
ui	0.88	0.26	−0.10	0.64	0.88	0.83	−1.02	−0.34	−0.42	0.52	0.09	0.02	0.12	0.15	0.15	0.16	0.05	0.07
mp	2.15*	1.86	1.71	1.98	2.23	2.10	2.46	0.75	0.17	0.52	0.44	0.37	0.43	0.44	0.41	0.47	0.14	0.03
Panel C5: Interest Rate & Monetary Policy																		
trms	−0.80	−1.07	−1.40	−4.57**	−4.28**	−4.75**	−7.50***	−10.24***	−10.45***	0.52	0.58	0.39	0.69	0.61	0.58	0.82	1.06	1.08
ltychg	0.06	0.24	−0.38	−3.92*	−3.16	−3.60	−9.49***	−14.31***	−13.79***	0.52	0.34	0.06	0.46	0.31	0.33	0.66	0.94	0.90
mjsummp	−1.03	−0.81	−0.81	−1.94	−1.67	−2.31	−4.15**	−6.76***	−6.21**	0.52	0.36	0.36	0.64	0.41	0.37	0.65	0.94	0.86
mpbs	−2.45**	−2.38*	−2.48*	−2.18	−2.09	−2.75*	−5.67***	−7.43***	−6.69**	0.52	0.51	0.52	0.46	0.43	0.45	0.75	0.95	0.83
mjodysu2	−2.32**	−1.78	−1.71	−2.18	−2.12	−2.29	−3.91**	−4.88**	−4.72**	0.52	0.35	0.34	0.42	0.40	0.42	0.67	0.82	0.80
mpbsort	−4.25***	−4.35***	−4.25***	−4.32**	−4.36**	−4.91**	−5.77***	−7.03***	−6.67**	0.52	0.53	0.52	0.53	0.53	0.55	0.64	0.76	0.72
emvmon	−6.11***	−6.46***	−6.62***	−7.36***	−7.81***	−7.83***	−5.67**	−7.77***	−9.23***	0.52	0.55	0.56	0.62	0.63	0.63	0.44	0.60	0.68
uts	−0.08	−0.20	−0.60	−2.56	−1.98	−1.99	−4.78**	−7.55***	−6.63**	0.52	0.43	0.12	0.42	0.25	0.25	0.53	0.81	0.68
emvir	−5.50***	−6.17***	−6.52***	−7.57***	−7.94***	−8.09***	−6.42***	−7.68***	−8.34***	0.52	0.57	0.58	0.66	0.67	0.68	0.53	0.63	0.68
mpjkff4	−1.96	−1.70	−1.85	−1.28	−1.35	−2.25	−5.87**	−6.94**	−5.88*	0.52	0.45	0.46	0.31	0.33	0.36	0.74	0.87	0.67
mpjkcbi	0.79	0.94	0.87	0.61	0.65	0.71	3.76*	3.02	3.36	0.52	0.58	0.52	0.35	0.37	0.39	0.73	0.58	0.64
mpmar	−2.16*	−1.67	−1.55	−1.81	−1.85	−2.81*	−4.91**	−5.62**	−4.85	0.52	0.36	0.33	0.39	0.40	0.40	0.67	0.76	0.63
mpjkcbimed	−0.53	−0.62	−0.49	−0.04	−0.26	−0.08	2.00	2.06	2.28	0.52	0.58	0.34	0.02	0.11	0.03	0.49	0.50	0.55
mjlsapu4	2.41**	2.16**	2.49**	0.81	1.13	0.62	−0.12	−3.11	−3.63	0.52	0.45	0.46	0.13	0.17	0.09	0.02	0.39	0.45
mpjkspnew	0.69	0.31	0.43	1.24	1.11	1.39	3.18*	1.21	1.76	0.52	0.16	0.20	0.47	0.39	0.41	0.73	0.26	0.36
mpjkpc	−1.08	−0.58	−0.51	−0.94	−1.03	−1.14	−0.70	1.82	1.26	0.52	0.21	0.18	0.32	0.34	0.37	0.22	0.45	0.30
upr	−3.01*	−3.17	−2.64	−2.98*	−3.47*	−3.63*	−0.49	2.34	2.74	0.52	0.55	0.30	0.34	0.35	0.36	0.05	0.21	0.25
mpbsortfit	1.85	2.48**	2.04	2.50	2.90	2.61	−1.24	−3.39	−2.22	0.52	0.58	0.35	0.42	0.42	0.37	0.14	0.38	0.23
mpmarinf	1.07	1.15	0.21	1.41	1.73	2.03	−1.94	−2.53	−1.86	0.52	0.56	0.03	0.20	0.21	0.25	0.20	0.26	0.18
mjratesu1	−1.55	−1.51	−1.91	−1.40	−1.32	−1.72	−2.36	−2.36	−1.10	0.52	0.51	0.46	0.33	0.31	0.31	0.44	0.44	0.18
mpjksporg	4.41**	4.44**	4.37**	2.78	3.19	3.09	3.71	2.49	1.49	0.52	0.53	0.52	0.32	0.34	0.33	0.39	0.26	0.15
mjdelphu3	−0.60	−0.32	−0.59	0.72	0.72	1.09	−1.48	−0.34	0.56	0.52	0.19	0.23	0.22	0.22	0.26	0.24	0.05	0.08
mpjkmed	−1.04	−0.51	−0.52	−1.19	−1.17	−1.40	−2.09	0.39	−0.23	0.52	0.18	0.19	0.39	0.38	0.41	0.59	0.09	0.05
mpjkpm	−1.34*	−0.92	−0.83	−1.15	−1.24	−1.40	−1.96	0.57	0.06	0.52	0.31	0.27	0.37	0.39	0.42	0.57	0.13	0.01

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Table IA.9 — Continued

	Panel 1: Risk Premia									Panel 2: Sharpe Ratios								
	F_{1-1}	F_{1-2}	F_{1-3}	F_{1-4}	F_{1-5}	F_{1-6}	F_{1-7}	F_{1-8}	F_{1-9}	$\text{SR}_{F_{1-1}}$	$\text{SR}_{F_{1-2}}$	$\text{SR}_{F_{1-3}}$	$\text{SR}_{F_{1-4}}$	$\text{SR}_{F_{1-5}}$	$\text{SR}_{F_{1-6}}$	$\text{SR}_{F_{1-7}}$	$\text{SR}_{F_{1-8}}$	$\text{SR}_{F_{1-9}}$
	Panel C6: Political Uncertainty																	
emvpol	−5.76***	−6.17***	−6.40***	−6.75***	−7.27***	−7.41***	−5.06**	−6.45**	−7.62***	0.52	0.56	0.57	0.60	0.61	0.62	0.40	0.51	0.59
gpr(acts)	−0.93	−1.49	−1.39	−1.23	−1.58	−1.62	−1.88	−2.20	−2.16	0.52	0.53	0.46	0.41	0.39	0.40	0.47	0.54	0.53
emvtrad	−3.34	−4.13	−4.70*	−4.83	−5.18	−5.32	−3.58	−4.90	−5.00	0.52	0.58	0.52	0.54	0.55	0.56	0.37	0.50	0.50
emvfisc	−4.69***	−5.30***	−5.45***	−5.30***	−5.69***	−5.80***	−3.88*	−4.42*	−5.00*	0.52	0.57	0.58	0.57	0.58	0.59	0.38	0.43	0.48
gpr	−1.30	−1.79	−1.83	−1.29	−1.60	−1.49	−1.30	−1.88	−1.79	0.52	0.57	0.58	0.39	0.40	0.36	0.32	0.45	0.43
epu	−4.27***	−4.67***	−4.69***	−4.00**	−4.53***	−4.23**	−1.33	−2.57	−3.81	0.52	0.56	0.57	0.48	0.49	0.45	0.13	0.24	0.34
gepu	−3.13**	−2.87*	−2.88*	−1.43	−1.69	−1.46	1.56	−1.73	−3.17	0.52	0.46	0.46	0.22	0.25	0.21	0.18	0.18	0.29
gpr(thrts)	−1.45	−1.63	−1.85	−1.24	−1.41	−1.14	−0.35	−1.18	−1.10	0.52	0.57	0.52	0.34	0.36	0.26	0.08	0.25	0.23
gepuppp	−2.82**	−2.52*	−2.54*	−1.20	−1.45	−1.23	1.96	−1.19	−2.40	0.52	0.44	0.44	0.20	0.23	0.19	0.23	0.13	0.23
	Panel C7: Behavioral																	
dtoy	11.68***	13.47***	13.96***	13.57***	14.31***	14.69***	17.10***	16.09***	15.55***	0.52	0.58	0.59	0.57	0.58	0.60	0.68	0.64	0.62
dtoat	11.77***	13.66***	14.25***	13.63***	14.42***	14.95***	17.26***	16.51***	15.64***	0.52	0.58	0.59	0.56	0.58	0.59	0.67	0.64	0.61
disag	3.25**	3.47**	3.45**	5.22***	5.20***	5.37***	7.43***	4.29*	4.24*	0.52	0.55	0.55	0.75	0.74	0.75	0.95	0.50	0.50
sent	−0.92	−0.63	−0.77	−0.94	−0.84	−1.29	−1.16	0.13	1.37	0.52	0.31	0.32	0.39	0.33	0.28	0.25	0.03	0.24

Table IA.10
Macro-Financial Risk Factors and the Tangency Portfolio (Full)

The table presents univariate spanning regressions of the optimal tangency portfolio return (R_{VM}; left panels), the spanned component (R_S; mid panels), and the unspanned component (R_U; right panels) on the priced macro-financial risk factors. For each panel, we report the constant, α, the regression coefficient, β, and the explained variation, R^2 (in percent). The tangency portfolio, its components and the candidate risk factors entering the regressions are first de-noised using the three-pass method, so that all variables are return-based. This implies that the αs are meaningful objects to assess, in the sense of Barillas and Shanken (2017). We provide the description of the candidate risk factors in Table IA.3, in the Internet Appendix. ***, ** and * correspond to a rejection of the null hypothesis of zero at the 1%, 5% and 10% confidence levels, respectively, where standard errors are calculated using Newey and West (1987).

	α_{VM}	β_{VM}	R^2_{VM}	α_S	β_S	R^2_S	α_U	β_U	R^2_U
				Panel A: Tradable					
bdstrad	0.11***	−0.73***	39.90	0.05***	−0.68***	55.95	0.06***	−0.05	0.62
jkpdebiss	0.13***	−0.95***	27.54	0.07***	−0.89***	39.07	0.06***	−0.06	0.36
ficar	0.14***	0.72***	21.57	0.08***	0.79***	42.07	0.07***	−0.07	0.70
eqstrad	0.14***	−0.50***	21.53	0.08***	−0.52***	37.82	0.06***	0.02	0.13
comstrad	0.15***	−0.57***	19.22	0.08***	−0.59***	33.76	0.06***	0.02	0.12
eqcar	0.15***	−0.76***	17.37	0.10***	−0.45***	9.66	0.05***	−0.31***	9.85
fxcar	0.15***	0.38***	16.24	0.08***	0.47***	39.46	0.07***	−0.09*	2.77
jkpstrmv	0.15***	0.53***	16.20	0.10***	0.37***	12.82	0.05***	0.16***	4.85
fxstrad	0.16***	−0.41***	9.74	0.10***	−0.51***	24.17	0.07***	0.10	1.86
irstrad	0.16***	−0.34***	8.96	0.10***	−0.41***	21.14	0.06***	0.07	1.29
jkplolev	0.16***	−0.29***	8.88	0.12***	−0.02	0.08	0.05***	−0.27***	25.26
bab	0.17***	0.28***	6.58	0.11***	0.15***	2.94	0.06***	0.13***	4.91
jkpacc	0.17***	0.40***	5.35	0.12***	−0.22***	2.65	0.05***	0.62***	42.92
jkpseas	0.17***	−0.28***	4.93	0.10***	−0.65***	43.72	0.07***	0.37***	29.55
vrp	0.17***	0.34***	4.85	0.11***	0.28***	5.11	0.06***	0.07	0.60
comcar	0.18***	0.15***	2.51	0.11***	0.20***	7.30	0.06***	−0.05*	0.97
jkpsize	0.18***	−0.11	1.71	0.12***	−0.12***	3.17	0.06***	0.01	0.03
jkpval	0.18***	0.07**	1.63	0.12***	0.01	0.03	0.06***	0.06***	4.34
jkpmom	0.18***	0.06*	1.45	0.12***	−0.05**	1.28	0.06***	0.11***	14.59
jkpprofg	0.18***	0.09	1.39	0.12***	0.03	0.32	0.06***	0.06	1.79
jkpinv	0.18***	0.10**	1.17	0.12***	−0.17***	5.96	0.06***	0.27***	29.96
jkpqual	0.18***	−0.07	0.80	0.12***	−0.17***	7.01	0.06***	0.10**	4.68
jkpprof	0.18***	0.03	0.09	0.12***	−0.09	0.97	0.06***	0.12***	3.77
jkplorsk	0.18***	0.01	0.02	0.12***	−0.16***	13.33	0.06***	0.17***	30.05
				Panel B: Non-tradable Macro-Financial					
				Panel B1: Financial Uncertainty					
move	0.11***	−0.73***	39.55	0.04***	−0.79***	75.17	0.07***	0.06	0.94
ted	0.11***	−0.81***	38.92	0.05***	−0.81***	63.80	0.06***	0.01	0.01
avgcor	0.12***	−0.54***	31.44	0.06***	−0.55***	52.63	0.06***	0.01	0.03
emvfincri	0.13***	−0.65***	28.83	0.07***	−0.59***	38.46	0.06***	−0.06	0.80
impvar	0.13***	−0.35***	27.57	0.06***	−0.44***	69.16	0.07***	0.09***	5.55
fsi	0.15***	−0.59***	18.26	0.08***	−0.73***	45.20	0.07***	0.14**	3.43
vix/vxo	0.15***	−0.26***	17.72	0.07***	−0.37***	56.85	0.07***	0.11***	9.86
finunc	0.15***	−0.41***	15.57	0.08***	−0.52***	40.42	0.07***	0.11**	3.70
mf1	0.16***	−0.72***	13.97	0.10***	−0.49***	10.59	0.05***	−0.23***	4.61
geqrv	0.16***	−0.46***	13.13	0.08***	−0.69***	48.92	0.07***	0.24***	11.74
mf2	0.16***	0.50***	12.30	0.09***	0.60***	28.76	0.07***	−0.10	1.69
gfc	0.16***	0.14***	10.45	0.09***	0.21***	38.88	0.07***	−0.07***	9.31
perunc	0.17***	0.28***	4.80	0.12***	−0.03	0.09	0.05***	0.31***	19.65
corp	0.17***	−0.22***	4.46	0.10***	−0.38***	22.34	0.07***	0.17***	8.58
shtint	0.18***	0.31**	1.96	0.11***	1.04***	35.30	0.07***	−0.73***	35.64
mf3	0.18***	−0.03	0.03	0.12***	−0.10	0.52	0.06***	0.06	0.50
				Panel B2: Liquidity					
psliq	0.16***	0.44***	12.60	0.10***	0.45***	21.13	0.06***	−0.01	0.01
icap	0.16***	0.16***	9.15	0.09***	0.27***	41.49	0.07***	−0.11***	13.88
noise	0.17***	−0.34***	7.48	0.10***	−0.52***	27.44	0.07***	0.17***	6.39
				Panel B3: Crash Risk					
skew	0.11***	0.97***	39.01	0.05***	0.98***	64.01	0.06***	−0.01	0.01
adbear	0.14***	−0.26***	23.93	0.07***	−0.32***	59.65	0.07***	0.06**	4.67
tail	0.15***	1.12***	17.96	0.08***	1.27***	37.32	0.07***	−0.15**	1.07

(continued over page)

Table IA.10 — Continued

	α_{VM}	β_{VM}	R^2_{VM}	α_S	β_S	R^2_S	α_U	β_U	R^2_U
	Panel B4: Macro								
dei	0.10***	−1.78***	43.41	0.07***	−1.01***	22.66	0.03***	−0.77***	26.86
ygap	0.14***	−0.37***	23.12	0.06***	−0.49***	66.02	0.08***	0.12***	8.35
realunc	0.14***	−0.70***	22.15	0.08***	−0.72***	37.13	0.06***	0.01	0.03
emvout	0.14***	−0.43***	19.87	0.08***	−0.45***	35.42	0.06***	0.02	0.17
emvov	0.15***	−0.41***	19.12	0.08***	−0.45***	36.94	0.06***	0.04	0.56
emvinf	0.15***	−0.40***	14.11	0.09***	−0.48***	33.54	0.07***	0.08*	2.13
macunc	0.16***	−0.45***	13.35	0.09***	−0.53***	29.43	0.07***	0.08	1.26
emvfx	0.18***	−0.23*	2.00	0.11***	−0.42***	10.34	0.06***	0.18**	4.13
ogap	0.18***	−0.29***	1.77	0.11***	−0.58***	11.49	0.06***	0.29***	5.95
ui	0.18***	−0.09	0.20	0.12***	−0.13	0.72	0.06***	0.04	0.15
mp	0.18***	0.04	0.04	0.12***	0.69***	16.79	0.06***	−0.65***	30.42
	Panel B5: Interest Rate & Monetary Policy								
trms	0.08***	−0.94***	54.25	0.05***	−0.66***	43.68	0.03***	−0.28***	15.58
ltychg	0.11***	−0.49***	37.70	0.07***	−0.34***	29.07	0.04***	−0.15***	11.97
mjsummp	0.12***	−1.00***	34.37	0.07***	−0.84***	39.53	0.05***	−0.16***	2.78
mpbs	0.12***	−0.86***	31.94	0.05***	−0.97***	65.33	0.07***	0.11**	1.67
mjodysu2	0.13***	−1.12***	29.25	0.06***	−1.15***	49.70	0.06***	0.03	0.06
mpbsort	0.14***	−0.65***	24.15	0.07***	−0.80***	58.96	0.07***	0.15**	4.22
emvmon	0.14***	−0.42***	21.35	0.08***	−0.41***	33.19	0.06***	−0.01	0.03
uts	0.14***	−0.58***	21.15	0.09***	−0.48***	23.33	0.05***	−0.10**	2.12
emvir	0.14***	−0.46***	21.15	0.08***	−0.51***	42.55	0.07***	0.05	0.95
mpjkff4	0.14***	−0.65***	21.05	0.07***	−0.81***	53.67	0.07***	0.17***	4.59
mpjkcbi	0.15***	1.01***	18.83	0.09***	0.98***	28.50	0.06***	0.03	0.06
mpmar	0.15***	−0.67***	18.14	0.08***	−0.83***	44.29	0.07***	0.15***	3.17
mpjkcbimed	0.15***	1.12***	14.16	0.10***	0.61***	6.89	0.05***	0.50***	9.57
mjlsapu4	0.16***	−0.46***	9.23	0.12***	0.05	0.17	0.04***	−0.51***	37.58
mpjkspnew	0.17***	0.60***	5.86	0.11***	0.58***	8.67	0.06***	0.03	0.04
mpjkpc	0.17***	0.57***	4.03	0.12***	0.21*	0.85	0.06***	0.37***	5.46
upr	0.18***	0.18**	2.79	0.12***	−0.06	0.49	0.05***	0.24***	16.40
mpbsortfit	0.18***	−0.20***	2.49	0.12***	−0.13**	1.79	0.06***	−0.07	0.91
mpmarinf	0.18***	−0.15**	1.56	0.12***	−0.19***	4.07	0.06***	0.04	0.38
mjratesu1	0.18***	−0.24**	1.48	0.11***	−0.78***	25.03	0.07***	0.54***	24.62
mpjksporg	0.18***	0.13	1.07	0.11***	0.51***	27.55	0.07***	−0.39***	31.89
mjdelphu3	0.18***	0.10	0.30	0.12***	−0.26***	3.55	0.06***	0.36***	13.66
mpjkmed	0.18***	−0.09	0.12	0.12***	−0.25**	1.48	0.06***	0.16**	1.25
mpjkpm	0.18***	0.02	0.01	0.12***	−0.33***	2.40	0.06***	0.36***	5.68
	Panel B6: Political Uncertainty								
emvpol	0.15***	−0.37***	15.85	0.09***	−0.40***	29.61	0.06***	0.03	0.30
gpr(acts)	0.16***	−1.10***	13.21	0.09***	−1.29***	29.46	0.07***	0.19	1.34
emvtrad	0.16***	−0.42***	11.78	0.09***	−0.52***	28.72	0.07***	0.10*	2.05
emvfisc	0.16***	−0.38***	10.65	0.09***	−0.50***	29.18	0.07***	0.12**	3.24
gpr	0.16***	−0.86***	8.53	0.10***	−1.23***	28.34	0.07***	0.37**	5.35
epu	0.17***	−0.26***	5.47	0.11***	−0.29***	11.29	0.06***	0.03	0.31
gepu	0.17***	−0.22***	3.94	0.11***	−0.16***	3.18	0.06***	−0.07	1.13
gpr(thrts)	0.18***	−0.42**	2.53	0.11***	−0.74***	13.10	0.07***	0.33***	5.25
gepuppp	0.18***	−0.19**	2.48	0.12***	−0.13**	1.94	0.06***	−0.06	0.76
	Panel B7: Behavioral								
dtoy	0.15***	0.21***	17.86	0.07***	0.30***	58.75	0.08***	−0.09***	10.83
dtoat	0.15***	0.20***	16.97	0.07***	0.28***	57.64	0.08***	−0.09***	11.42
disag	0.16***	0.49***	11.51	0.09***	0.75***	43.66	0.07***	−0.26***	10.85
sent	0.18***	0.34***	2.57	0.12***	−0.26***	2.41	0.05***	0.60***	26.54

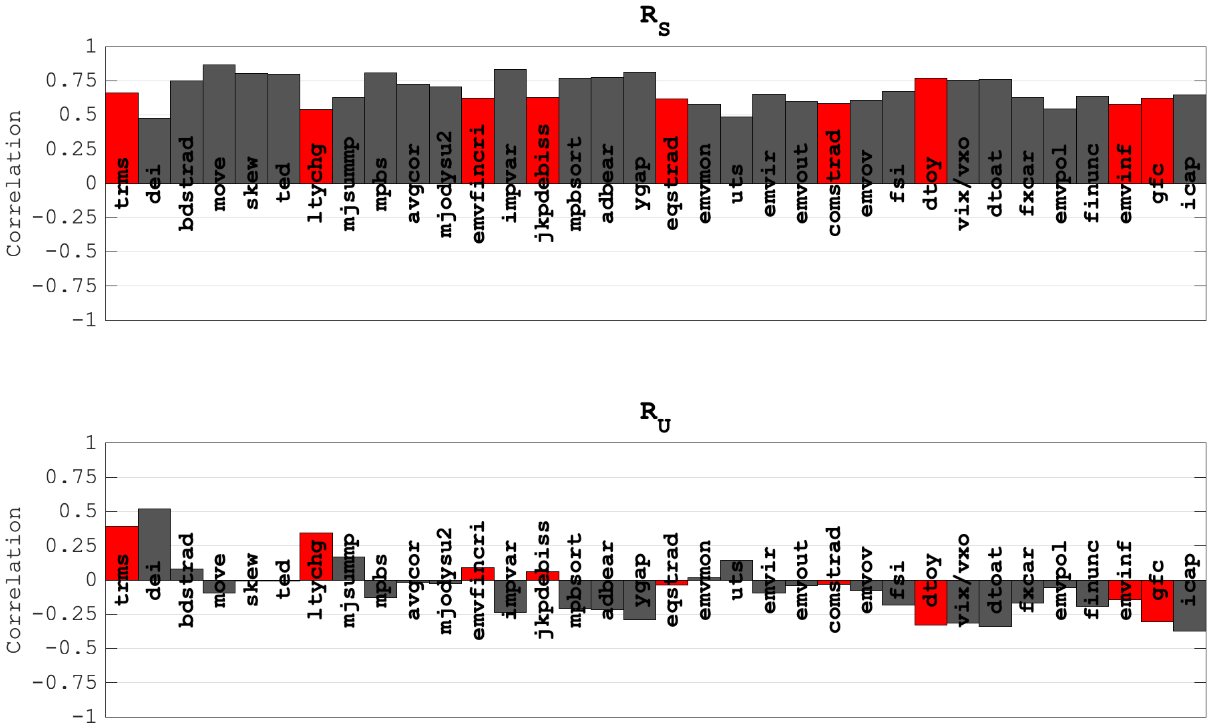

Figure IA.10. R_S **and** R_U **Candidate Factor Correlations.** The figure presents correlations between the decomposition components of the optimal nine-latent-factor tangency portfolio, R_S and R_U (see Table 5), and the de-noised candidate macro-financial factors, computed in Table 7. Specifically, for the spanned, R_S, and unspanned, R_U, decomposition components and the return-based candidate factors, all de-noised from the third-pass of the Giglio and Xiu (2021) procedure, we present the pairwise correlations between the respective factor returns for the 34 factors with a significant risk premium at the 5% level. Those factors displayed in red comprise the reduced-form nine-factor model which spans the optimal tangency portfolio. These factors are identified using a LASSO estimation to shrink the cross-section of candidate factors (see Figure 9). The sample is 07/1983–12/2023, at monthly frequency.