On the Macroeconomic Foundations of the Anomaly Zoo

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Abstract

We apply modern asset pricing methods to estimate risk premia for 192 candidate macroeconomic factors using a broad cross section of equity style portfolios. A dozen macroeconomic factors carry statistically significant risk premia under a framework that accounts for multiple testing. Models that include tradable mimicking portfolios for these factors frequently outperform leading multifactor models in explaining CAPM anomalies and fully account for the abnormal returns earned by factor momentum strategies. Our findings point to a link between economic fluctuations and asset prices, with the empirically strongest factors tied to housing starts and real personal consumption of services.

JEL classification: G11, G12

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1 Introduction

Prior studies document hundreds of asset pricing anomalies, i.e., patterns in average stock returns that cannot be explained by the Capital Asset Pricing Model (CAPM). A central question in asset pricing is whether the abnormal returns associated with these anomalies reflect rational compensation for systematic risk, behavioral biases, or spurious patterns arising from data mining. Macro-finance theories predict that expected returns vary through time and across assets in ways that are linked to macroeconomic conditions (Cochrane, 2005). All else equal, an asset that pays off poorly in bad times is less desirable and should have a higher risk premium than an asset that pays off poorly in good times.

Despite these theoretical predictions, prior literature offers limited support for the idea that macroeconomic variables are priced in the cross section of stock returns or that macroeconomic risk underlies stock return anomalies. Much of the existing evidence is based on a relatively narrow set of factors and return anomalies. As a representative example, consider the industrial production factor proposed by Chen, Roll, and Ross (1986). Liu and Zhang (2008) show that industrial production growth explains over half of momentum profits, and Cooper and Priestley (2011) find that this factor explains several investment-related anomalies. Momentum- and investment-related strategies, however, represent only a small subset of the so-called "anomaly zoo" (Cochrane, 2011; McLean and Pontiff, 2016; Feng, Giglio, and Xiu, 2020; Hou, Xue, and Zhang, 2020; Chen and Zimmermann, 2022; Martin and Nagel, 2022). And there is limited evidence on whether the explanatory power of industrial production growth generalizes to other anomalies, or how its performance compares with that of other macroeconomic variables showing similar empirical promise.

In this paper, we consider a comprehensive set of 192 macroeconomic variables to assess whether macroeconomic factors are priced and the extent to which the priced macroeconomic risks account for CAPM anomalies. Our empirical approach builds on the three-pass procedure for risk premium estimation and mimicking portfolio construction developed by Giglio and Xiu (2021). We find that 46 macroeconomic variables—including several related to consumption, employment, and housing—command significant risk premia in a large cross section of equity portfolios. After adjusting for multiple testing using formal false-discovery-rate control (Benjamini and Hochberg, 1995), 12 variables remain statistically significant and constitute a core set of priced macroeconomic factors for subsequent analysis. Two-factor models that combine the market factor with a single macroeconomic factor render up to 70% of CAPM anomalies insignificant, outperforming leading models including the Fama-French (2016) six-factor model and the Hou-Xue-Zhang (2015) q-factor model. Models based on real personal consumption of services or housing starts also completely explain the factor momentum strategies of Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023). Taken together, our findings suggest a meaningful link between economic fluctuations and asset prices.

We diverge from existing literature in both the scope of our empirical analysis and the estimation methods. Prior studies often rely on the Fama-MacBeth (1973) two-pass procedure or mimicking portfolio methods (Breeden, Gibbons, and Litzenberger, 1989; Lamont, 2001) for risk premium estimation. Giglio and Xiu (2021) demonstrate that the two-pass procedure yields biased estimates of the risk premia for nontraded factors (e.g., macroeconomic factors) owing to measurement error and omitted control factors with significant risk prices. The mimicking portfolio approach suffers from a related omitted variable bias if the set of assets used in the projection fails to span all relevant risk factors. Giglio and Xiu (2021) propose a three-pass estimator that mitigates these biases and exploits the information contained in a large cross section of test assets. Their three-pass procedure extracts latent factors using principal component analysis (PCA), estimates the risk premia of the resulting latent factors, and then projects the nontradable factors onto the span of the latent pricing factors. The nontradable factors' risk-premium estimates are given by linear combinations of the risk prices of the latent factors. Following Nucera, Sarno, and Zinna (2024), we augment the Giglio and Xiu (2021) procedure by replacing the first-pass PCA approach to latent factor estimation with the risk premium principal component analysis (RP-PCA) approach of Lettau and Pelger (2020a,b). Whereas standard PCA extracts latent factors that explain common time-series variation in test asset returns, RP-PCA identifies latent factors that capture both time-series variation in returns and cross-sectional variation in average returns.

We use the augmented three-pass procedure to extract six latent factors from the excess returns of 865 equity portfolios over the period from 1970 to 2024. All six latent factors exhibit large Sharpe ratios, ranging from 0.37 to 1.20 on an annualized basis. The first latent factor closely resembles the market factor. The remaining five factors earn statistically significant CAPM alphas. Spanning regressions indicate that several of these factors contain pricing information not captured by the Fama-French (2016) six-factor model or the Hou-Xue-Zhang (2015) q-factor model, suggesting that the SDF estimated from our test assets contains substantial incremental information relative to leading asset pricing models.

We next examine whether a broad set of macroeconomic variables are priced in the cross section of stock returns. Our sample consists of 192 variables taken from the FRED-QD database compiled by McCracken and Ng (2021). We rely on this database because it is comprehensive, publicly available, and updated in real time; its variables are considered economically important a priori (e.g., Stock and Watson, 2012); and it reduces researcher discretion in variable selection.

We find that many macroeconomic factors are priced under the augmented Giglio and Xiu (2021) three-pass procedure. Of the 192 candidate macroeconomic variables, 46 command statistically significant risk premia. Following McCracken and Ng (2021), we group the macroeconomic variables into ten categories: NIPA; industrial production; employment and unemployment; housing; inventories, orders, and sales; prices; earnings and productivity; money and credit; consumer sentiment; and non-household balance sheets. The categories with the largest number of significantly priced variables are NIPA, employment and unemployment, housing, and prices. The signs of the risk premia associated with these macroeconomic variables are also generally consistent with economic intuition. For example, growth rates in real personal consumption expenditures, industrial production, and various employment indicators are positively priced, but changes in unemployment rates are negatively priced. We find mixed evidence on the pricing of inflation risk, with some price indices carrying negative risk prices and others positive.

The large number of candidate macroeconomic variables necessitates careful attention to multiple hypothesis testing. When testing 192 risk premia simultaneously, conventional significance levels may overstate the strength of the evidence because some statistically significant findings can arise by chance. We adjust for multiple testing using the false discovery rate (FDR) procedure of Benjamini and Hochberg (1995). This approach controls the expected proportion of false discoveries among the set of statistically significant results, providing a natural framework for large-scale testing problems such as ours. We focus on an FDR threshold of 20%, which strikes a balance between statistical stringency and power in an exploratory setting with many economically motivated hypotheses. After applying FDR control, 12 macroeconomic variables remain statistically significant. These variables are distributed across five categories—NIPA (1), employment and unemployment (2), housing (7), prices (1), and non-household balance sheets (1)—and form the core set for our subsequent analyses.

We next investigate the extent to which the associated macroeconomic risks explain stock return anomalies. We construct our anomaly sample using data from the Global Factor Data (GFD) website (Jensen, Kelly, and Pedersen, 2023). From this database, we use capped-value-weighted returns for tercile portfolios formed using univariate sorts on 153 characteristics for U.S. firms. We apply two inclusion criteria: (i) each anomaly must have complete return data from 1970 to 2024, and (ii) the CAPM alpha of the long-short anomaly portfolio must be positive and statistically significant. These criteria yield a final sample of 104 CAPM anomalies. Following Hou, Xue, and Zhang (2015), we classify the anomalies into six categories: momentum, value, investment, profitability, intangibles, and trading frictions.

For each of the 12 macroeconomic variables that survive FDR control, we construct a tradable factor-mimicking portfolio by projecting the variable onto the six latent RP-PCA factors and combine the macroeconomic factor with the market factor to form a two-factor model. We then estimate the alpha of each long-short anomaly portfolio relative to each two-factor macroeconomic model. We assess model performance primarily using two metrics: the average percentage reduction in alpha relative to the CAPM, and the number of anomalies that remain positive and statistically significant under the two-factor specification.

We find considerable evidence that macroeconomic factors help explain stock return anomalies. For example, the two-factor model incorporating the mimicking portfolio for personal consumption expenditures on services (PCESVx) reduces the average anomaly alpha by 58.7% and renders 70 (67%) of the 104 anomaly alphas insignificant. The two-factor model based on privately owned housing starts (HOUST) yields a 61.4% reduction in the average anomaly alpha and explains 71 (68%) of the 104 anomalies. By comparison, the Carhart (1997) four-factor model, the Fama-French (2015) five-factor model, the Fama-French (2016) six-factor model, and the Hou-Xue-Zhang (2015) q-factor model reduce the average anomaly alpha by 31.7%, 45.8%, 54.7%, and 55.5%, respectively, rendering 16, 46, 48, and 58 anomaly alphas insignificant. In short, many two-factor macroeconomic models, despite their more parsimonious specification, outperform leading asset pricing models in explaining stock return anomalies.

Across the anomaly categories, macroeconomic factors explain a substantial share of the abnormal returns for momentum, value, investment, and trading frictions anomalies. For example, incorporating the housing starts (HOUST) factor reduces the average alpha of the 12 value anomalies by 98.3%, with none remaining statistically significant. The two-factor model with the personal consumption expenditures on services (PCESVx) factor reduces the average alpha of the seven momentum anomalies by 95.1%, with only one alpha remaining statistically significant. Macroeconomic factors also reconcile many of the anomalies in the investment and trading frictions categories. The strong performance within the trading frictions category is noteworthy, as most anomalies in this group are based on liquidity or short-term market movements. The only category for which macroeconomic factors perform poorly is intangibles, which includes several strategies related to return seasonality. The average alpha reduction across these anomalies is modest, and around half remain statistically significant.

Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023) document strong evidence of factor momentum: anomalies that performed well in the recent past continue to perform well in the future. They argue that factor momentum arises from persistence in investor sentiment.

We explore an alternative, risk-based explanation for factor momentum. Consistent with Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023), we find significant evidence of time-series and cross-sectional factor momentum in our sample. More important, we show that exposures to macroeconomic risks account for the profits to factor momentum strategies.

Cochrane (2005, p. xiv) argues that "the central and unfinished task of absolute pricing is to understand and measure the sources of aggregate or macroeconomic risk that drive asset prices." Prior studies identify several macroeconomic variables that are priced in the cross section of stock returns, including industrial production growth (Chen, Roll, and Ross, 1986; Liu and Zhang, 2008; Cooper and Priestley, 2011), inflation risk (Chen, Roll, and Ross, 1986; Boons, Duarte, de Roon, and Szymanowska, 2020), investment growth (Cochrane, 1996), long-run consumption of stockholders (Malloy, Moskowitz, and Vissing-Jørgensen, 2009), capital share of aggregate income (Lettau, Ludvigson, and Ma, 2019), and labor market tightness (Kuehn, Simutin, and Wang, 2017). Despite the growing body of evidence, the prevailing view among academics and practitioners is that macroeconomic variables offer limited explanatory power for the cross section of stock returns, particularly in comparison with financial or market-based variables.

We contribute to this literature by studying a comprehensive set of macroeconomic variables, and more important, by identifying a set of robustly priced macroeconomic risks. A key distinction relative to prior work is our use of the three-pass procedure to estimate the risk prices for macroeconomic factors. This innovation effectively mitigates the omitted variable and measurement error biases inherent in traditional two-pass and mimicking portfolio methods, which tend to overstate statistical significance. The set of priced macroeconomic variables documented in our analysis offers a valuable foundation for developing new theoretical macro-finance models. Our findings also create opportunities for empirical research on whether the macroeconomic risks priced in U.S. equities are similarly priced in other countries and asset classes. And our approach to mimicking portfolio construction provides a useful tool for identifying the economic drivers of managed portfolio performance (e.g., mutual funds and hedge funds).

Our paper contributes to the debate over whether the abnormal returns for capital market anomalies reflect compensation for systematic risk, behavioral biases, or data mining. Harvey, Liu, and Zhu (2016) and Harvey (2017) argue that most published anomalies are likely false discoveries attributable to data mining. Chen and Zimmermann (2022) and Jensen, Kelly, and Pedersen (2023) challenge this view by showing that the majority of anomalies replicate in both U.S. and international markets. A separate strand of literature attributes anomalies to behavioral biases and views them as evidence of market inefficiency. For example, McLean and Pontiff (2016) show that anomaly returns decay by about 58% out of sample and present evidence consistent with behavioral explanations. Daniel, Hirshleifer, and Sun (2020) propose a three-factor model incorporating two behavioral factors and show that their model outperforms existing asset pricing models in explaining anomalies. Our paper advances the case for risk-based explanations by showing that macroeconomic risk plays a central role in pricing a broad array of anomalies.

Our study also relates to the growing literature on meta-analysis of stock market anomalies. Recent studies have examined whether investors and analysts exploit information in stock anomalies (Engelberg, McLean, and Pontiff, 2020; Guo, Li, and Wei, 2020; Wang, Yan, and Zheng, 2024; McLean, Pontiff, and Reilly, 2025), whether anomaly returns exhibit momentum (Wang, Yan, and Zheng, 2021; Ehsani and Linnainmaa, 2022; Arnott, Kalesnik, and Linnainmaa, 2023), whether volatility-managed anomaly portfolios generate superior performance (Cederburg, O'Doherty, Wang, and Yan, 2020; DeMiguel, Martín-Utrera, and Uppal, 2024), and whether machine learning models based on anomaly variables outperform traditional statistical models (Freyberger, Neuhierl, and Weber, 2020; Gu, Kelly, and Xiu, 2020; Li, Rossi, Yan, and Zheng, 2025). We contribute to this literature by characterizing the macroeconomic risks underlying the anomaly zoo.

2 Methods

Our objectives are to estimate risk premia and to construct mimicking portfolios for nontradable, macroeconomic factors. To this end, we follow the three-pass estimation approach of Giglio and Xiu (2021), with an adjustment to the first-pass latent factor estimation step as proposed by Nucera, Sarno, and Zinna (2024).

The Giglio and Xiu (2021) three-pass estimation approach involves (i) extracting a set of latent asset pricing factors from a broad panel of excess returns, (ii) computing the risk premia on these latent factors using a cross-sectional regression of average excess returns on the estimated factor loadings, and (iii) estimating the risk premium and mimicking portfolio for a given nontraded factor via a time-series regression of the nontraded factor innovations on the latent factors. This method offers two key advantages in our setting. First, it addresses the omitted variable bias inherent in the standard mimicking portfolio approach (e.g., Breeden, Gibbons, and Litzenberger, 1989; Lamont, 2001), in which an arbitrary selection of portfolios for the projection makes risk premium estimates sensitive to research design and biased if the chosen portfolios fail to span the true underlying risk factors. The three-pass estimator overcomes this limitation by efficiently extracting latent factors from a sufficiently large cross section to capture all relevant sources of risk. Second, because the three-pass approach removes measurement error in the nontradable factors through projection onto the factor space, it mitigates the concerns with measurement error bias that plague other approaches for risk premium estimation (e.g., Fama and MacBeth (1973) regressions). The measurement error concern is acute in our setting, as macroeconomic variables tend to exhibit low absolute correlations with asset returns (i.e., they are noisy proxies for the true candidate factors).

Because the three-pass method of Giglio and Xiu (2021) relies on PCA to estimate the latent factors, the choice of regularization technique matters for the properties of the resulting mimicking portfolios. Nucera, Sarno, and Zinna (2024) argue that a compelling alternative regularization technique is the RP-PCA approach of Lettau and Pelger (2020a,b). Whereas PCA identifies latent factors that explain the time-series variation in test asset returns, RP-PCA selects factors that capture both time-series variation in returns and cross-sectional variation in average returns. This distinction is economically important: asset pricing theory restricts the relation between expected excess returns and betas, suggesting that an approach targeting both first and second moments better aligns with theory. Lettau and Pelger (2020a,b) demonstrate that RP-PCA delivers more efficient estimates of latent factors, better identifies weak factors with high Sharpe ratios, and improves out-of-sample performance relative to standard PCA.

2.1 Latent Factor Estimation

We begin by describing the PCA and RP-PCA approaches to latent factor estimation. We have a balanced panel of excess returns for N test assets (indexed by $n = 1, 2, \ldots, N$) observed over T periods (indexed by $t = 1, 2, \ldots, T$). Excess returns, denoted $R_{n,t}$, follow a standard factor structure under the assumptions of the arbitrage pricing theory (APT):

$$R_{n,t} = F_t \psi_n' + \varepsilon_{n,t}, \tag{1}$$

where F_t is a $1 \times K$ vector of latent factor realizations in period t, ψ_n is a $1 \times K$ vector of latent factor loadings for asset n, and $\varepsilon_{n,t}$ is the idiosyncratic return component. In matrix form, the model is expressed as

$$R = F\psi' + \varepsilon, \tag{2}$$

where R is the $T \times N$ matrix of excess returns, F is the $T \times K$ matrix of latent factors, ψ is the $N \times K$ matrix of loadings, and ε is the $T \times N$ matrix of idiosyncratic errors. Standard PCA extracts the latent factors (principal components) and loadings (eigenvectors) through an eigenvalue decomposition of the sample covariance matrix of excess returns:

$$\Sigma_{PCA} = \frac{1}{T} R'R - \overline{R}'\overline{R}, \tag{3}$$

where $\overline{R}$ denotes the $1 \times N$ vector of test asset average excess returns. The estimated factor loadings, $\widehat{\psi}$, are proportional to the K eigenvectors associated with the K largest eigenvalues of Σ_{PCA}. The PCA factors are then estimated from a regression of the test asset excess returns on the factor loadings:

$$\widehat{F} = R\widehat{\psi}(\widehat{\psi}'\widehat{\psi})^{-1}. \tag{4}$$

The PCA approach specifically identifies the K (orthogonalized) factors with the largest variances as estimates of the actual latent factors. PCA thus focuses entirely on explaining the second moments of test asset returns. We also note that there is a well-known indeterminacy in PCA and other latent factor estimation methods: rotating the estimated factors and counter-rotating the estimated loadings leads to a model that is observationally equivalent to the original model.

Lettau and Pelger (2020a,b) propose a related approach that modifies standard PCA by incorporating information on the first moments of test asset returns, that is, the cross-sectional pricing errors. The appeal of their approach lies in its close alignment with asset pricing theory, as factors are required to explain simultaneously the time-series and cross-sectional properties of stock returns. Their RP-PCA procedure is based on an eigenvalue decomposition of

$$\Sigma_{RP-PCA} = \frac{1}{T} R'R + \omega\overline{R}'\overline{R}, \tag{5}$$

where ω is a penalty parameter that governs the extent to which mean asset returns are weighted in the estimation. The case of $\omega = -1$ corresponds to standard PCA estimation. Lettau and Pelger (2020a,b) also demonstrate that applying an eigenvalue decomposition to Eq. (5) and then estimating the factors from a regression of excess returns on the eigenvectors as in Eq. (4) is equivalent to solving the following minimization problem:

$$\min_{F,\psi} \frac{1}{NT} \sum_{n=1}^{N} \sum_{t=1}^{T} \left(R_{n,t} - F_t \psi_n'\right)^2 + \omega \frac{1}{N} \sum_{n=1}^{N} \left(\overline{R}_n - \overline{F}\psi_n'\right)^2, \tag{6}$$

where $\overline{R}_n$ denotes the average excess return for asset n and $\overline{F}$ is the $1 \times K$ vector of average factor realizations. The first term in the minimization reflects the ability of the latent factors to explain time-series variation in asset returns, and the second term captures their ability to explain average returns. Larger values of ω place more emphasis on the latent factors' ability to produce small cross-sectional pricing errors. In practice, RP-PCA with $\omega > 0$ tends to identify factors with larger Sharpe ratios than those produced by standard PCA because such factors generate lower pricing errors (Gibbons, Ross, and Shanken, 1989). But the restriction that the latent factors must also explain second moments guards against the identification of spurious factors that are unrelated to realized returns.

2.2 RP-PCA Model Evaluation

The RP-PCA estimation approach requires two key design choices: the "optimal" number of latent factors (K) and the RP-PCA penalty value (ω). We select these parameters based on existing evidence from the literature and a combination of statistical and economic criteria.

For a given value of ω, there are several statistical methods for selecting the appropriate number of factors. Lettau and Pelger (2020b), for example, rely on the Onatski (2010) estimator. This estimator exploits the property that the eigenvalues associated with systematic factors in the sample covariance matrix diverge to infinity, whereas the largest eigenvalues for idiosyncratic factors cluster near a single point. Giglio and Xiu (2021) introduce an estimator that balances model fit and parsimony for panels with large N and large T.[1] Giglio and Xiu (2021) also recommend a diagnostic based on visual inspection of the scree plot of ordered eigenvalues.

In addition to these statistical criteria, we compare the models using economic metrics. Following Lettau and Pelger (2020b) and Nucera, Sarno, and Zinna (2024), we construct the SDF implied by each candidate set of latent factors (i.e., for alternative values of K). If the latent factors are orthogonalized (as they are in all applications below), the SDF takes the form

$$M_t = 1 - \sum_{k=1}^{K} \frac{\overline{F}_k}{\widehat{\sigma}^2_{F,k}} \left(\widehat{F}_{k,t} - \overline{F}_k\right), \tag{8}$$

[1] The Giglio and Xiu (2021) estimator for the number of latent factors is

$$\widehat{K} = \underset{1 \le k \le K_{\max}}{\arg\min} \left(\frac{\lambda_k}{NT} + jP_{GX} \operatorname{med}\{\lambda_1, \lambda_2, \ldots, \lambda_{K_{max}}\}(\log N + \log T)(N^{-1/2} + T^{-1/2}) \right), \tag{7}$$

where K_{max} is the maximum number of factors, λ_k is the kth largest eigenvalue of the covariance matrix, and P_{GX} is an overfitting penalty parameter. Following Giglio and Xiu (2021), we consider small (0.25), medium (0.50), and large (0.75) values for P_{GX}, and we set $K_{max} = 20$.

where $\overline{F}_k$ and $\widehat{\sigma}^2_{F,k}$ denote the mean and variance, respectively, of latent factor k. The associated maximum Sharpe ratio for an economy spanned by the K latent factors is equal to the standard deviation of M_t. The maximum Sharpe ratio is therefore increasing in K, but we can use the relation in Eq. (8) to assess a given factor's marginal impact on the Sharpe ratio in our search for a parsimonious factor representation.

The final set of economically motivated diagnostics follows from familiar regression-based factor model representations. For each test asset, we estimate the following time-series regression using OLS:

$$R_{n,t} = \alpha_n + \widehat{F}_t B_n' + e_{n,t}, \tag{9}$$

where α_n is the pricing error for asset n and B_n is the asset's $1 \times K$ vector of factor loadings. Lettau and Pelger (2020b) emphasize that under the RP-PCA approach, the estimate of ψ_n in Eq. (1) differs from the estimate of B_n in Eq. (9) for two reasons: (i) only Eq. (9) includes an intercept and (ii) even with the intercept in Eq. (9) constrained to be zero, $\widehat{\psi}_n = \widehat{B}_n$ only if $\omega = 0$. Lettau and Pelger (2020b) note, however, that the differences are negligible in practice. We assess model performance as a function of K using the average ratio of idiosyncratic variance to total variance:

$$\text{IVOL}(K) = \frac{1}{N}\sum_{n=1}^{N}\frac{\widehat{\sigma}^2_{e,n}}{\widehat{\sigma}^2_n}, \tag{10}$$

and the root-mean-square pricing error:

$$\text{RMSPE}(K) = \left(\frac{1}{N}\sum_{n=1}^{N}\widehat{\alpha}^2_n\right)^{1/2}. \tag{11}$$

We also consider the R^2 value and the mean absolute pricing error from the cross-sectional regression (without an intercept) of average test asset excess returns on the estimated factor loadings.

In our main specification, we use RP-PCA estimation with the penalty parameter $\omega = 10$, and we compare our results with those from standard PCA estimation with $\omega = -1$. We select $\omega = 10$ based on Lettau and Pelger's (2020b) evidence that this penalty value produces favorable out-of-sample properties for models estimated from a cross section of equity portfolios similar to our sample across a wide range of values for K. We further confirm that the model with $\omega = 10$ performs well across the economic diagnostics described above. In robustness tests, we demonstrate that our main findings—including the number of macroeconomic factors with significant risk premia and the pricing performance of the corresponding mimicking portfolios—are stable across a wide range of ω values.

2.3 The Augmented Three-Pass Method

In this section, we detail our approach to risk premium estimation and mimicking portfolio construction for macroeconomic factors using the augmented three-pass method.

2.3.1 Risk Premia Estimation

In the first pass, we extract the latent factors and the test assets' loadings on these factors from a broad cross section of excess stock returns. We compute the eigenvectors based on the eigenvalue decomposition of Σ_{RP-PCA} in Eq. (5) and recover the factor space following Eq. (4). To facilitate an economic interpretation of the factors, we follow Nucera, Sarno, and Zinna's (2024) approach of sequentially orthogonalizing the factors using the Gram-Schmidt method. We also rescale the factors so that the first factor has the same variance as the market factor and require all factors to have positive means.

We obtain the factor loadings via time-series regressions of the test asset excess returns on the latent factors. As described in Lettau and Pelger (2020b) and Nucera, Sarno, and Zinna (2024), for these regressions to recover loadings consistent with the model in Eq. (1), they must be estimated with transformed data. Define $\widetilde{R}_{n,t} = R_{n,t} + (\sqrt{\omega+1}-1)\overline{R}_n$ and $\widetilde{F}_{k,t} = \widehat{F}_{k,t} + (\sqrt{\omega+1}-1)\overline{F}_k$. The time-series regressions are given by

$$\widetilde{R}_{n,t} = \widetilde{F}_t \psi_n' + \widetilde{\varepsilon}_{n,t}. \tag{12}$$

In the second pass, we estimate risk prices for the latent factors using a cross-sectional regression of average test asset excess returns on the estimated factor loadings:

$$\overline{R}_n = \widehat{\psi}_n \gamma' + a_n, \tag{13}$$

where γ is the $1 \times K$ vector of latent factor risk premia. Because the untransformed latent factors are excess returns, the estimated prices of risk are equal to the corresponding means, i.e., $\widehat{\gamma}_k = \overline{F}_k$.

In the third pass, we project each candidate nontraded macroeconomic factor onto the span of the latent pricing factors. Define $G^d_{j,t} = G_{j,t} - \overline{G}_j$ as the demeaned value of nontraded factor j at time t and $\widehat{F}^d_{k,t} = \widehat{F}_{k,t} - \overline{F}_k$ as the demeaned value of latent factor k. The regression is given by

$$G^d_{j,t} = \widehat{F}^d_t \eta_j' + \vartheta_{j,t}, \tag{14}$$

where $\widehat{F}_t^d$ is the $1 \times K$ vector of the demeaned latent factors and η_j is the $1 \times K$ vector of factor exposures for the nontraded factor on the latent factors. The risk premium for macroeconomic factor j is estimated by combining the second-pass estimates of the latent factor risk prices with the third-pass estimates of the loadings:

$$\widehat{\lambda}_j^G = \widehat{\gamma}\widehat{\eta}_j'. \tag{15}$$

An important property of the Giglio and Xiu (2021) estimator of the macroeconomic factor's risk premium is its invariance to any nonsingular rotation of the latent factors. This result is critical given that only the span of the latent factors is identified. To understand this property, consider the observationally equivalent model with rotated factors given by $\widehat{F}_t^r = \widehat{F}_t H^{-1}$ and counter-rotated loadings given by $\widehat{\psi}_n^r = \widehat{\psi}_n H'$, where H is a $K \times K$ nonsingular matrix. The latent factor risk premia from the rotated model are $\widehat{\gamma}^r = \widehat{\gamma} H^{-1}$, and the loadings for the nontraded factor on the latent factors are $\widehat{\eta}_j^r = \widehat{\eta}_j H'$. The macroeconomic factor risk premium estimate is thus unchanged from the original model:

$$\widehat{\lambda}_j^{Gr} = \widehat{\gamma} H^{-1}(\widehat{\eta}_j H')' = \widehat{\gamma}\widehat{\eta}_j' = \widehat{\lambda}_j^G. \tag{16}$$

2.3.2 Mimicking Portfolio Construction

The mimicking portfolio for the macroeconomic factor is

$$\widehat{G}_{j,t} = \widehat{F}_t \widehat{\eta}_j'. \tag{17}$$

This construction has three key features. First, the mimicking portfolio is itself an excess return because it is a linear function (without an intercept) of the latent excess return factors. This property allows $\widehat{G}_{j,t}$ to be used as a tradable factor in standard time-series asset pricing models. Second, the projection of the macroeconomic factor onto the latent factor space removes noise from the original factor and retains only the components relevant for asset pricing. Third, the mimicking portfolio estimator also exhibits the rotation-invariance property. In the preceding example with rotated factors and counter-rotated loadings, the mimicking portfolio is

$$\widehat{G}_{j,t}^r = \widehat{F}_t H^{-1}(\widehat{\eta}_j H')' = \widehat{F}_t \widehat{\eta}_j' = \widehat{G}_{j,t}. \tag{18}$$

3 Data

We describe the data sources and construction below, with additional details on variable names, descriptions, and transformations in the internet appendix. All data series are constructed at a quarterly frequency over the period from 1970:Q1 to 2024:Q4.

3.1 Test Assets for the Augmented Three-Pass Method

We compile a large dataset of 865 characteristic-sorted equity portfolios to estimate latent factors and macroeconomic risk premia. The sample combines portfolios from two sources. First, we use monthly returns for 315 value-weighted portfolios from Kenneth French's data library.[2] The portfolios include 25 double-sorted portfolios formed on size and each of book-to-market equity, operating profitability, investment, momentum, short-term reversal, long-term reversal, accruals, beta, variance, and residual variance; 35 double-sorted portfolios formed on size and net share issues; and 30 industry portfolios. Second, we augment these 315 portfolios with 550 portfolios from the Open Source Asset Pricing (OSAP) anomaly database described in Chen and Zimmermann (2022).[3] We begin with 179 sets of value-weighted quintile portfolios formed on individual firm characteristics and then drop the 69 sets that lack complete data coverage over our 1970–2024 sample period. This screen yields monthly returns for 110 sets of characteristic-sorted quintile portfolios (i.e., 550 total portfolios). Both sets of test portfolios are widely used in empirical research and together provide a comprehensive representation of the style effects and cross-sectional return predictors examined in prior literature.

We obtain data on the monthly risk-free rate from Kenneth French's website. For each of the 865 characteristic-sorted portfolios, we construct a quarterly buy-and-hold excess return series. We do so by compounding the monthly returns for a given portfolio and the risk-free asset separately over each quarter and then computing the difference.

3.2 Macroeconomic Factors

We consider a broad set of 192 nontradable, macroeconomic factors from the FRED-QD database described in McCracken and Ng (2021).[4] All variables are available at a quarterly frequency. The

[2] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for making these data available.

[3] See https://www.openassetpricing.com/. We use the October 2025 data release. We thank Andrew Chen and Tom Zimmermann for making these data available.

[4] The FRED-QD database is updated monthly and available at https://www.stlouisfed.org/research/economists/mccracken/fred-databases. We use the November 2025 data release.

FRED-QD database represents a substantial extension of the FRED-MD database (McCracken and Ng, 2016), which is at a monthly frequency and thus omits data on gross domestic product, consumption, investment, government spending, and other macroeconomic series that come from the National Income and Product Accounts (NIPA). Because many of these macroeconomic variables have close links to asset pricing theory, we opt to use the quarterly data. Both FRED-MD and FRED-QD are large macroeconomic databases designed for empirical applications with big data. They are publicly available, updated in real time through the FRED database, and span the major macroeconomic aggregates, coincident indicators, and leading indicators.

The full FRED-QD database contains time series for 245 macroeconomic variables across 14 categories. Given our focus on assessing premia related to macroeconomic risks, we remove variables in four categories related to financial risks: interest rates, household balance sheets, exchange rates, and stock markets. We also drop series without full coverage over the 1970–2024 sample period. The filters yield a balanced panel of 192 macroeconomic time series grouped into 10 categories: NIPA (22); industrial production (16); employment and unemployment (49); housing (11); inventories, orders, and sales (8); prices (47); earnings and productivity (11); money and credit (14); consumer sentiment (1); and non-household balance sheets (13).

Because not all series in the FRED-QD database are stationary in levels, we apply the transformations suggested by McCracken and Ng (2021) designed to render the series stationary. For a given series $\{z_t\}_{t=-1}^{T}$, the transformation codes take the following forms: (1) no transformation, (2) Δz_t, (3) $\Delta^2 z_t$, (4) $\log(z_t)$, (5) $\Delta \log(z_t)$, (6) $\Delta^2 \log(z_t)$, and (7) $z_t/z_{t-1} - 1$. We report the transformation code used for each series in the internet appendix. Following the standard practice in the literature (e.g., Giglio and Xiu, 2021; Nucera, Sarno, and Zinna, 2024), we estimate an AR(1) model for each transformed series and define our nontradable, macroeconomic factors as the corresponding AR(1) innovations.

3.3 Style Factors

We also use quarterly versions of several tradable asset pricing factors. We obtain the data to construct the market (*MKT*), size (*SMB*), value (*HML*), profitability (*RMW*), investment (*CMA*), and momentum (*UMD*) factors from Kenneth French's website. As with the test assets, we calculate the quarterly frequency factors by separately compounding the monthly returns for the long and short legs of each factor and then taking the difference. We obtain the quarterly versions of alternative size (*ME*), profitability (*ROE*), and investment (*IA*) factors from Lu Zhang's website.[5]

[5]See https://global-q.org/factors.html. We thank Lu Zhang for making these data available.

The benchmark models used for comparison with our macroeconomic models are the CAPM (*MKT* factor), Carhart (1997) four-factor model (*MKT*, *SMB*, *HML*, and *UMD*), Fama-French (2015) five-factor model (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*), Fama-French (2016) six-factor model (adds *UMD* to the five-factor model), and Hou-Xue-Zhang (2015) q-factor model (*MKT*, *ME*, *ROE*, and *IA*).

3.4 Anomaly Portfolios

We construct the anomaly portfolios using data on U.S. factor returns from the GFD website (Jensen, Kelly, and Pedersen, 2023).[6] These portfolios are distinct from the 865 characteristic-sorted portfolios used to estimate the latent factors, thereby mitigating concerns about sample overlap in factor construction and model evaluation.

We begin with the 153 sets of capped-value-weighted anomaly tercile portfolios from GFD. For each characteristic, we compute quarterly excess returns for a long-short portfolio by taking the difference in returns between the high- and low-expected return terciles. We drop four excess return series that lack complete data coverage over the 1970–2024 sample period, leaving 149 anomaly portfolios for the main analysis. Jensen, Kelly, and Pedersen (2023) classify the strategies in their dataset into 13 themes. We consolidate these themes into six broader anomaly categories related to momentum (momentum theme), value (value theme), investment (accruals, debt issuance, and investment themes), profitability (profit growth, profitability, and quality themes), intangibles (low leverage and seasonality themes), and trading frictions (low risk, size, and short-term reversal themes). The 149 strategies are distributed across the six categories as follows: momentum (8), value (14), investment (35), profitability (40), intangibles (23), and trading frictions (29). We use this classification to organize and summarize many of our key results.

To construct the anomaly sample used for model evaluation, we focus on the subset of long-short strategies that exhibit positive and statistically significant CAPM alphas at the 5% level over our sample period. This restriction yields a final sample of 104 long-short anomaly portfolios.

4 Results

In this section, we present and discuss our empirical findings. We begin by characterizing the latent factor space based on the RP-PCA approach in the first pass of the augmented Giglio and Xiu (2021) procedure (Section 4.1). We next estimate risk premia for a comprehensive set of macroeconomic

[6]See https://jkpfactors.com/. We thank Theis Jensen, Bryan Kelly, and Lasse Pedersen for making these data available.

factors (Section 4.2). We then address multiple hypothesis testing and identify the subset of factors that survive formal FDR adjustment (Section 4.3). Finally, we construct mimicking portfolios for the retained factors and evaluate their ability to explain stock return anomalies (Section 4.4) and factor momentum strategies (Section 4.5).

4.1 Latent Factor Space

We first determine an appropriate dimension (K) for the factor space under our baseline RP-PCA specification. We apply RP-PCA to the cross section of 865 equity portfolios for $K = 1, 2, \ldots, 20$, using $\omega = 10$ (as introduced in Section 2.2). Table I reports the optimal number of latent factors based on the Onatski (2010) and Giglio and Xiu (2021) tests for both RP-PCA ($\omega = 10$) and standard PCA ($\omega = -1$). All tests for RP-PCA point to a relatively modest dimension for the factor space, but there is some disagreement in the estimates. The Onatski (2010) test indicates three latent factors, whereas the Giglio and Xiu (2021) tests suggest between four and six, depending on the level of the applied overfitting penalty. The implied dimensions of the factor space are also broadly similar under the RP-PCA and PCA approaches.

Figure 1 presents several additional diagnostics. Panel A shows a scree plot of the largest 20 ordered eigenvalues of Σ_{RP-PCA}. The first eigenvalue is substantially larger than the others, consistent with the presence of a strong systematic factor. Panel B focuses on the eigenvalues ranked from 4 to 20. One would typically look for a pronounced drop in eigenvalues to determine the cutoff point for the dimension of the model, but the observed decline is relatively gradual. As such, the scree plot alone does not point to an obvious number of factors.

We ultimately proceed with $K = 6$ based on the upper end of the range suggested by the statistical tests summarized in Table I. Although a model with fewer factors may be defensible, Giglio and Xiu (2021) show that their estimator remains consistent provided K is no smaller than the true dimension of the factor space. The choice of $K = 6$ is consistent with related work using similarly broad cross sections to extract latent factors. For example, Lettau and Pelger (2020b) use five latent factors extracted from 370 equity portfolios, and Giglio and Xiu (2021) use seven factors extracted from 647 portfolios of equities, bonds, and currencies. Panels C and D of Figure 1 provide additional economic justification for our baseline choice. Panel C shows the annualized maximum Sharpe ratio, and Panel D shows the annualized mean absolute pricing error from the cross-sectional regression in Eq. (13), both as functions of K. Neither diagnostic points to large economic gains from the addition of factors beyond six.

In the internet appendix, we present and discuss several economic metrics to justify our base case choice of $\omega = 10$ in the RP-PCA estimation. For models with $K = 6$, we examine how the maximum Sharpe ratio, the average idiosyncratic variance in Eq. (10), and the average absolute cross-sectional model pricing error in Eq. (13) vary across values of ω ranging from -1 to 50. In general, higher values of ω yield higher Sharpe ratios and lower average pricing errors, but at the cost of increased idiosyncratic variance. Our choice of $\omega = 10$ offers a favorable balance across these effects.

We summarize in Table II the properties of the first six latent factors estimated using both RP-PCA and standard PCA. The table reports the average excess return, the standard deviation of the excess return, and the Sharpe ratio for each factor. All statistics are annualized. The first factor in each specification exhibits much higher variance than the remaining factors. And as we show below, it has a very high correlation with *MKT*. Thus, both first factors have a natural economic interpretation as aggregate "market" proxies.

The properties of the remaining factors differ across the RP-PCA and PCA approaches. Under PCA, the factors are ranked in order of their standard deviations by construction. The second PCA factor has a low mean (0.49%) and the lowest Sharpe ratio (0.13) in comparison with all other factors. This factor explains substantial time-series variation in test asset returns, but carries an economically small price of risk. The highest Sharpe ratio under PCA of 0.52 is associated with the third factor.

The Sharpe ratios for the extracted RP-PCA factors are generally higher than those for the PCA factors. The RP-PCA factors are ranked according to their ability to explain both time-series variation in returns and differences in average returns. Thus, unlike PCA, the RP-PCA factor ordering is not determined solely by variance. The second factor has lower standard deviation than does the third, and the fourth factor has lower standard deviation than does the fifth. The Sharpe ratios for the second (0.71) and fourth (1.20) factors are both high, indicating the importance of these factors in explaining the cross section of stock returns.

Table III provides evidence on the relation between the six RP-PCA factors and traditional asset pricing factors. We report the results from spanning regressions of the latent factors on the market factor (Panel A), the six Fama-French (2016) factors (Panel B), and the four Hou-Xue-Zhang (2015) factors (Panel C). The alphas and alpha t-statistics from the regressions indicate whether the pricing information in each latent factor is subsumed by the standard factors (Barillas and Shanken, 2017; Fama and French, 2018). The loadings and R^2 values characterize the direction and strength of the time-series relations across the two types of factors.

As expected, the first RP-PCA factor closely resembles the market factor. As shown in Panel A, this factor has an insignificant CAPM alpha, a market beta near one, and an R^2 of 96%. The remaining five latent factors earn statistically significant CAPM alphas at the 5% level or better. These factors also exhibit CAPM R^2 values below 3%, suggesting that they are effectively orthogonal to the market. The alphas for the second and third factors are positive but statistically insignificant relative to the Fama-French (2016) and Hou-Xue-Zhang (2015) models. Neither factor has a clear interpretation as a substitute for a single factor in one of the multifactor models, as both load significantly on multiple factors. The fourth through sixth latent factors earn statistically significant alphas at the 5% level relative to the two multifactor benchmarks, providing strong evidence that they contain pricing information that is not spanned by the standard models. The fourth latent factor loads positively on momentum and exhibits a substantially higher R^2 under the Fama-French (2016) benchmark than under the Hou-Xue-Zhang (2015) benchmark. The fifth and sixth latent factors have modest R^2s in all cases.

The results in Table III suggest that the RP-PCA factors contain pricing information that is not subsumed by standard factor models. For comparison, we present a version of Table III based on the PCA factors in the internet appendix. In contrast to RP-PCA, none of the six PCA factors earns a significantly positive alpha at the 5% level relative to either the Fama-French (2016) model or the Hou-Xue-Zhang (2015) model, and many of the point estimates of alpha are negative. This contrast further supports the use of RP-PCA to characterize the latent factor space.

Figure 2 reports results from regressing the excess returns of the standard factors on the latent RP-PCA (Panel A) and PCA (Panel B) factors. Each bar in the plot summarizes a series of six sequential regressions, in which one additional latent factor is added at each step. The figure highlights each latent factor's marginal contribution to explaining the time-series variation in the known factors. In both panels, the six latent factors capture nearly all variation in the market (*MKT*) and size (*SMB* and *ME*) factors, with cumulative R^2s of 94% or higher. The latent factors explain less of the variation in the profitability (*RMW* and *ROE*) and investment (*CMA* and *IA*) factors, but the cumulative R^2s still exceed 44% in all cases. The proportion of the R^2 attributable to each latent factor also aids in the economic interpretation of those factors. In Panel A, for example, the first RP-PCA factor explains nearly all variation in the market factor. The second and fourth latent factors capture large fractions of the variation in the profitability (i.e., *RMW* and *ROE*) and momentum (*UMD*) factors, respectively. Under RP-PCA, the fourth factor contributes most to explaining momentum. But the fifth latent factor plays this role under PCA. Thus, the ordering of the factors differs across the RP-PCA and PCA methods.

Our results demonstrate that RP-PCA with six factors effectively recovers the latent factor space and offers an economically reasonable representation of the SDF. The latent RP-PCA factors are not spanned by the factors from leading multifactor models. They also earn higher Sharpe ratios and command a different economic interpretation than do latent PCA factors. In the next section, we estimate risk premia and construct mimicking portfolios for a broad sample of macroeconomic factors.

4.2 Macroeconomic Factor Risk Premia

In Table IV, we summarize the results from the third pass of the augmented Giglio and Xiu (2021) procedure. For each of the 192 candidate macroeconomic factors, the third pass involves projecting the macroeconomic variable onto the latent RP-PCA factor space following Eq. (14) and then estimating its risk premium by combining the macroeconomic variable's latent factor loadings with the second-pass latent factor risk prices following Eq. (15). Because the three-pass approach relies on latent factors that span the relevant sources of risk in the cross section, it alleviates concerns about omitted variable bias that affect alternative methods of risk premium estimation, including the standard two-pass and mimicking portfolio approaches. The third pass of the estimation also serves to denoise the candidate factors and to avoid the inflated risk prices attributable to measurement error that are common in two-pass estimation (e.g., Fama and MacBeth, 1973).

For each macroeconomic variable, Table IV reports the estimated risk premium, its asymptotic standard error, and the associated t-statistic.[7] The table also presents the R^2 from the projection of the macroeconomic factor onto the latent factor space, the Sharpe ratio of the macroeconomic factor's mimicking portfolio, and the p-value from Giglio and Xiu's (2021) Wald test of the null hypothesis that the macroeconomic factor is weak (i.e., $\mathbb{H}_0 : \eta_j = 0$). The table reports results for the macroeconomic variables with statistically significant prices of risk at the 10% level or better, and the panels are grouped by macroeconomic variable category. The internet appendix provides results for the remaining macroeconomic variables and a version of Table IV based on PCA rather than RP-PCA in the first pass.

The results in Table IV yield two main takeaways. First, there is broad evidence that macroeconomic factors are priced in the cross section of stock returns. Of the 192 candidate factors, 46 have statistically significant risk premia based on conventional tests. The 46 variables span eight of the 10 broad macroeconomic categories, suggesting that the results are not driven by a narrow subset of highly correlated series. Second, although the expected sign of the risk premium is ambiguous for some variables, the vast majority of the estimated signs align with economic intuition and theoretical priors. Economic theory suggests that macroeconomic factors that covary negatively with the SDF (i.e., those that rise during good economic states when marginal utility is low) should command positive risk premia. Assets with

[7] We refer readers to Giglio and Xiu (2021) for details on the asymptotic distribution of the estimator of the macroeconomic factor risk premium $\widehat{\lambda}_j^G$ and the calculation of its asymptotic variance. The standard errors and t-statistics are robust to heteroskedasticity and autocorrelation in returns, and we use a Newey-West (1987) estimator with four lags.

greater exposure to such factors are riskier because they perform poorly during bad economic times.

In Panel A (NIPA category), for example, there are four macroeconomic factors with statistically significant risk premia: real personal consumption expenditures on services (PCESVx), real private fixed residential investment (PRFIx), real imports of goods and services (IMPGSC1), and real personal consumption expenditures (PCECC96). All four exhibit positive risk premia, consistent with models in which the corresponding economic activities are procyclical. From a theoretical perspective, aggregate consumption (PCECC96) represents perhaps the most natural candidate for a priced macroeconomic factor (e.g., Lucas, 1978; Breeden, 1979; Hansen and Singleton, 1983). The empirically strongest variable in this category, however, is real personal consumption expenditures on services, which carries the largest t-statistic among the four NIPA variables. Services consumption constitutes the dominant share of aggregate consumption expenditures—ranging from 64% to 76% of total consumption over our sample period—suggesting that PCESVx captures the bulk of the economically relevant variation in aggregate consumption risk.

Panel C (employment and unemployment) features 23 labor market variables with statistically significant risk premia, with a mix of positive and negative coefficients. The variables with positive coefficients relate to employment levels, hours worked, and hiring activity, while those with negative coefficients are generally related to unemployment rates and levels. The significance of total nonfarm payrolls (PAYEMS), total private industries employment (USPRIV), and total service-providing industries employment (SRVPRD) confirms that broad measures of labor market activity are priced in the cross section. A general theme that emerges, however, is that employment in private sector services is the primary driver of these results. The FRED-QD database covers 15 of the 17 major industry sectors tracked under nonfarm payrolls.[8] Among the four major sectors in the goods-producing industry group, only construction (USCONS) carries a significant risk premium, while mining (USMINE), durable goods manufacturing (DMANEMP), and nondurable goods manufacturing (NDMANEMP) do not. By contrast, six of the eight sectors within the private services-providing major group carry significant risk premia: professional and business services (USPBS), other services (USSERV), retail trade (USTRADE), financial activities (USFIRE), information services (USINFO), and education and health services (USEHS). None of the three government employment sectors (i.e., federal, state, and local government) is priced.

In Panel D (housing), the candidate macroeconomic factors are proxies for housing starts or building permit activity, and all 11 variables have positive risk prices. Priced housing risk is consistent with a broad theoretical literature linking housing to asset prices and expected returns. For many investors,

[8]The two major industry sectors missing from the FRED-QD database are transportation and warehousing and utilities.

housing represents a dominant component of wealth, and shocks to housing activity are closely tied to aggregate economic conditions (Lustig and Van Nieuwerburgh, 2005; Yogo, 2006; Piazzesi, Schneider, and Tuzel, 2007; Davis and Martin, 2009; Ma and Zhang, 2025).

Panel G (earnings and productivity) yields two closely related variables with significant negative risk premia: real compensation per hour in the nonfarm business sector (COMPRNFB) and in the business sector (RCPHBS). The expected sign of the risk premium for compensation growth is theoretically ambiguous, but the negative price is consistent with real compensation per hour being countercyclical (i.e., rising in downturns due to wage stickiness and labor market rigidities), such that assets covarying positively with compensation growth serve as hedges against bad economic times (Kuehn, Simutin, and Wang, 2017).

Our findings on the pervasiveness of priced macroeconomic risks and the alignment of estimated risk prices with theoretical priors are perhaps surprising in light of previous results in the literature. Nucera, Sarno, and Zinna (2024), for instance, apply methods similar to ours to measure the risk premia for financial, text-based, and macroeconomic factors in the cross section of currency returns. They find that relatively few macroeconomic factors are significantly priced and that many of the estimated risk premia carry signs inconsistent with economic theory.

The highest proportions and raw numbers of significantly priced macroeconomic factors occur in the housing (11 out of 11), employment and unemployment (23 out of 49), and NIPA (4 out of 22) categories. Each of the remaining categories contains at most three significantly priced variables. The second-to-last column of Table IV reports, for each macroeconomic factor, a p-value for the null hypothesis that the factor is weak (i.e., affects only a subset of the test assets). Among the four NIPA variables (Panel A) with significant risk premia, we reject the weak factor null at the 10% level for two and marginally fail to reject it for two others. Similarly, we reject the weak factor null for 10 of the 11 housing variables (Panel D). For the employment and unemployment variables (Panel C), in contrast, we fail to reject the weak factor null in most cases. These results suggest that NIPA and housing factors are relatively stronger and more pervasive in the cross section, whereas employment and unemployment risks influence a narrower subset of stocks.

The R^2 values from the projections of the macroeconomic factors onto the latent RP-PCA factors are generally low. These findings align with prior evidence (e.g., Giglio and Xiu, 2021; Nucera, Sarno, and Zinna, 2024) and indicate considerable measurement error in the macroeconomic variables. The R^2 values for the factors with statistically significant risk premia range from 1.73% to 28.85%. All but three of the R^2s are below 10%. Figure 3 shows the contribution of the individual latent factors to the overall R^2 for each macroeconomic variable. The primary driver of the explained variation is similar within each of the 10 broad categories, but differs across categories. The first latent factor is most relevant within the housing category. The second factor drives the explained variation in the industrial production, employment and unemployment, earnings and productivity, and money and credit groups. And the third factor is important for the prices category. The fourth, fifth, and sixth factors contribute materially to the explained variation in multiple series, but the category-specific roles of these factors are less pronounced.

In the internet appendix, we provide a detailed comparison of our results based on the augmented Giglio and Xiu (2021) procedure with those based on the conventional two-pass cross-sectional regression procedure. We find clear evidence that the measurement error and omitted variable biases cloud inferences under the two-pass procedure. Across several variants of the two-pass design, the number of macroeconomic factors with statistically significant risk premia always exceeds 100, and the estimated magnitudes are severely inflated (e.g., the median absolute risk price from the two-pass procedure is between 4.9 and 23.1 times larger than its three-pass counterpart, depending on the specification). These distortions stem primarily from measurement error in the macroeconomic factors, which leads to an attenuation bias in the first-pass factor loadings and inflated risk prices in the second-pass cross-sectional regression (e.g., Adrian, Etula, and Muir, 2014). The two-pass results are also highly sensitive to the choice of control factors, underscoring the omitted variable problem, and vary considerably across different sets of test assets, in line with the critique outlined by Lewellen, Nagel, and Shanken (2010). Collectively, these patterns confirm that inferences drawn from the standard two-pass method are unreliable and underscore the importance of the three-pass approach in identifying the robust set of priced macroeconomic factors documented in Table IV.

4.3 Multiple Testing Adjustment

Because we estimate risk premia for 192 macroeconomic variables simultaneously, conventional thresholds for statistical significance may overstate the strength of the evidence. As emphasized by Harvey (2017), large-scale testing in asset pricing applications raises concerns about data mining and spurious discoveries. At the same time, Harvey, Liu, and Zhu (2016) note that “a factor derived from a theory should have a lower hurdle than a factor discovered from a purely empirical exercise.” Many of the macroeconomic variables in our sample have clear foundations in macro-finance theory, suggesting that concerns about data mining may be less severe in this context. Nevertheless, we adopt a conservative benchmark and adjust for multiple hypothesis testing using the FDR procedure of Benjamini and

Hochberg (1995).

Let p_j denote the two-sided p-value associated with the test of the null hypothesis $\mathbb{H}_0 : \lambda_j^G = 0$ for macroeconomic variable j, and let $p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(J)}$ denote the ordered p-values ($J = 192$). For a given FDR level q, the Benjamini-Hochberg (1995) procedure identifies the largest rank r such that

$$p_{(r)} \leq \frac{r}{J} q, \tag{19}$$

and rejects all null hypotheses corresponding to $p_{(1)}, p_{(2)}, \ldots, p_{(r)}$. The procedure therefore controls the expected proportion of false discoveries among the rejected hypotheses at level q. The final column of Table IV reports the Benjamini-Hochberg (1995) adjusted p-value for the risk premium estimate, computed as

$$p_{BH(r)} = \min_{s \geq r} \left(\frac{J}{s} p_{(s)} \right). \tag{20}$$

Each adjusted p-value can be interpreted as the smallest FDR level at which the corresponding macroeconomic factor would be deemed statistically significant under the Benjamini-Hochberg (1995) procedure.

Figure 4 presents a histogram of the two-sided p-values across the 192 tests of macroeconomic risk premia. If none of the macroeconomic variables were priced, the p-values would be approximately uniformly distributed on $[0, 1]$. Instead, the distribution exhibits a pronounced excess mass at low p-values, particularly below 0.10. This pattern indicates that the global null of no priced macroeconomic risks is unlikely to hold uniformly and that a nontrivial subset of the variables are truly priced. Nonetheless, the large number of variables considered implies that some significant findings may arise by chance, underscoring the need for formal multiple-testing adjustment.

We set the FDR threshold at $q = 20\%$. This choice reflects a balance between statistical stringency and power in a setting with many economically motivated hypotheses. Controlling the FDR at this level reduces the number of statistically significant macroeconomic variables from 46 to 12 (i.e., the 12 variables in Table IV with p_{BH}-values of 0.20 or below).[9] These 12 variables span five of the 10 macroeconomic categories—NIPA (1), employment and unemployment (2), housing (7), prices (1), and non-household balance sheets (1). The housing category is particularly prominent, with seven of the 11 housing variables remaining statistically significant after applying FDR control. At the same time, the surviving factors are distributed across four additional macroeconomic groups, indicating that robust

[9]We note that the Benjamini-Hochberg (1995) approach to FDR control is known to be conservative. Alternative procedures that estimate the fraction of true null hypotheses (e.g., Storey, 2002) would likely identify a somewhat larger set of significant variables given the concentration of small p-values in Figure 4.

pricing evidence is not confined to a single segment of the macroeconomy. The mimicking portfolios for the 12 significant factors exhibit economically large absolute Sharpe ratios ranging from 0.62 to 1.28, and we reject the weak-factor null at the 10% level for all but one of these variables.

4.4 Macroeconomic Explanations of Asset Pricing Anomalies

We now evaluate the ability of the 12 FDR-significant macroeconomic factors to explain cross-sectional anomalies.

4.4.1 Anomaly Portfolios and Evaluation Criteria

We construct two-factor models, each comprising the market factor and the tradable mimicking portfolio for a given macroeconomic factor. We compare the performance of these models against several common benchmarks from the asset pricing literature. In the spirit of Fama and French (2015, 2016, 2017); Hou, Xue, and Zhang (2015); and Hou, Mo, Xue, and Zhang (2021), the tests summarize the ability of each model to account for patterns in average returns across a broad set of anomaly portfolios.

To form the anomaly portfolios for model evaluation, we start with the 149 sets of capped-value-weighted, characteristic-sorted tercile portfolios from GFD. For each characteristic, we construct a trading strategy that takes a long position in the tercile with high expected alpha and a short position in the tercile with low expected alpha. We then estimate a CAPM regression for each long-short portfolio i over the 1970 to 2024 sample period:

$$R_{i,t} = \alpha_i^C + \beta_i MKT_t + e_{i,t}, \tag{21}$$

and retain only the strategies with statistically significant alphas at the 5% level using one-tailed tests. Our use of a one-tailed cutoff for significance is motivated by prior empirical literature that establishes directional predictions for these effects (e.g., Jegadeesh and Titman (1993) show a positive relation between stock return momentum and abnormal returns). To assess statistical significance in these regressions and in the multifactor regressions below, we use heteroskedasticity and autocorrelation consistent standard errors based on a Newey-West (1987) lag parameter of four. The subset of trading strategies with significant CAPM alphas (104 in total) serves as the testing ground for model evaluation.

In Table V, we summarize the expected returns and CAPM regression results for these 104 anomaly portfolios. The anomaly portfolios are broadly distributed across the six categories: momentum (7), value (12), investment (30), profitability (27), intangibles (8), and trading frictions (20). The annualized alpha estimates range from 1.07% to 9.93% and generally correspond to economically large unexplained differences in average returns.

Let $\widehat{\alpha}_i^C$ denote the CAPM alpha for long-short strategy i, and let $\widehat{\alpha}_i$ be the alpha under a given alternative model. We use $\mathbb{A}[\cdot]$ to denote the average value across all 104 anomaly strategies. We summarize the performance of each model based on the following measures: (i) the average absolute alpha, $\mathbb{A}[|\widehat{\alpha}_i|]$, (ii) the average alpha, $\mathbb{A}[\widehat{\alpha}_i]$, and (iii) the average percentage reduction in the CAPM alpha:

$$\text{Average percentage reduction in } \widehat{\alpha}_i^C = \mathbb{A}\left[100\% \times \min\left(1 - \frac{\widehat{\alpha}_i}{\widehat{\alpha}_i^C}, 1\right)\right]. \tag{22}$$

The measure in Eq. (22) caps the reduction in CAPM alpha at 100% for cases in which $\widehat{\alpha}_i < 0$. We also report the number of alphas remaining statistically greater than zero at the 5% level based on one-tailed tests of $\mathbb{H}_0 : \alpha_i \leq 0$.

4.4.2 Benchmark Models

We present in Panel A of Table VI the performance metrics for the CAPM and the four benchmark multifactor models. Across the 104 anomaly strategies, the average CAPM alpha and average absolute CAPM alpha are both 5.00% per year (recall that all alpha estimates in Table V are positive). By construction, the average alpha reduction is 0.0%. The second row of Panel A summarizes the Carhart (1997) four-factor model's performance in explaining anomalies. The average Carhart (1997) absolute alpha is 3.28% per year, with an average alpha of 3.22%. The average percentage alpha reduction relative to the CAPM is 31.7%. The Carhart (1997) model explains 16 of the 104 CAPM anomalies, such that 88 alphas remain statistically significant at the 5% level. The Fama-French (2015) five-factor model provides noticeable improvements over the Carhart (1997) model on all performance metrics. The best performing benchmarks are the Fama-French (2016) six-factor model and Hou-Xue-Zhang (2015) q-factor model. These models deliver similar performance across the four measures. The Fama-French (2016) model produces the smallest average absolute alpha (2.10%). The Hou-Xue-Zhang (2015) model leads to the smallest average alpha (1.58%), the largest average CAPM alpha reduction (55.5%), and the fewest remaining anomalies (46).

Overall, the multifactor benchmarks offer substantial improvements over the CAPM. Given that these models are explicitly designed to reconcile CAPM anomalies, the quantitative results in Panel A of Table VI represent a high standard against which our macroeconomic models are evaluated.

4.4.3 Two-Factor Models with Macroeconomic Factors

For each macroeconomic factor j in Table IV that is significantly priced after accounting for multiple testing, we consider a model of the form

$$R_{i,t} = \alpha_i + \beta_i MKT_t + m_i \widehat{G}_{j,t} + e_{i,t}, \tag{23}$$

where $\widehat{G}_{j,t}$ is the mimicking portfolio for macroeconomic factor j as defined in Eq. (17) and m_i is the factor loading for strategy i. To facilitate comparison of the factor loading magnitudes across macroeconomic factors, we rescale each $\widehat{G}_{j,t}$ to match the standard deviation of the Fama-French size factor (*SMB*) over the sample period. The rescaling has no impact on the estimates of α_i or the summary measures of model performance.

We report in Panel B of Table VI the four summary performance measures for each two-factor model. Overall, the results provide evidence of macroeconomic foundations underlying the anomaly zoo. Most two-factor models with macroeconomic mimicking portfolios materially outperform the CAPM, and many yield performance metrics in line with those of the multifactor benchmarks built from tradable style factors. Based on average absolute alpha, the two best performing macroeconomic models are those based on housing starts in the Midwest census region (HOUSTMW) and real personal consumption expenditures on services (PCESVx). The average absolute alpha measures for these models—2.41% and 2.45%, respectively—are just marginally larger than the average absolute alphas for the Fama-French (2016) six-factor model (2.10%) and the Hou-Xue-Zhang (2015) q-factor model (2.12%), and are lower than those for all other benchmark models.

The two-factor models' performance is even stronger along the remaining three metrics. Four macroeconomic models (i.e., the PCESVx, USSERV, HOUST, and HOUSTMW models) outperform every multifactor benchmark based on average alpha, average CAPM alpha reduction, and number of significant anomalies. Moreover, three additional models (HOUSTNE, HOUSTS, and CUSR0000SAD) match or outperform the 46 significant anomalies produced by the best-performing multifactor model (i.e., the Hou-Xue-Zhang (2015) model).

The two-factor model based on housing starts in the Midwest census region (HOUSTMW) has the lowest average absolute alpha (2.41%), but ranks fourth on each of the other three measures. The model based on total new privately owned housing units started (HOUST) appears to be the overall top-performing model, ranking highest in terms of average alpha (0.21%), average CAPM alpha reduction (61.4%), and number of significant anomalies (33). This overall performance is nearly matched by the models with mimicking portfolios for real personal consumption expenditures on services (PCESVx) and employment level in other services (USSERV). The top models span multiple macroeconomic categories: NIPA (PCESVx), employment and unemployment (USSERV), and housing (HOUST and HOUSTMW).

The results contrast sharply with the prevailing view that macroeconomic variables have limited explanatory power for the cross section of returns. Prior studies typically focus on the ability of individual macroeconomic risks to explain patterns in average returns within a modest subset of the anomaly zoo. For example, Liu and Zhang (2008) construct a macroeconomic factor based on the growth rate of industrial production, and Adrian, Etula, and Muir (2014) consider innovations in broker-dealer leverage. The asset pricing applications in both studies link factor exposures to differences in average returns for size, book-to-market, and momentum portfolios. Lettau, Ludvigson, and Ma (2019) show that a factor based on the growth in the capital share of aggregate income exhibits explanatory power for equity portfolios sorted on size, book-to-market, investment, operating profitability, and long-run reversal. Studies offering more comprehensive evaluations of pricing performance across the anomaly zoo tend to focus on models with tradable factors formed on firm characteristics (e.g., Hou, Xue, and Zhang, 2015; Fama and French, 2016; Stambaugh and Yuan, 2017; Hou, Mo, Xue, and Zhang, 2021). Our findings suggest that models featuring interpretable macroeconomic risks perform on par with the most prominent multifactor benchmarks in the literature.

In the internet appendix, we demonstrate that our findings on the large number of macroeconomic variables with statistically significant risk premia, the performance of the corresponding factor-mimicking portfolios in resolving CAPM anomalies, and the categories of macroeconomic variables driving the results are robust to reasonable modifications of the empirical design. We consider a wide range of alternative values for the RP-PCA penalty parameter, the dimension of the latent factor space, and the test assets used for latent factor extraction.

Table VII examines the robustness of our findings to alternative constructions of the anomaly test assets. We repeat the main analysis from Table VI using three alternative anomaly samples: (i) 149 value-weighted tercile portfolios from GFD, (ii) 149 equal-weighted tercile portfolios from GFD, and (iii) 110 value-weighted quintile portfolios from OSAP.[10] For each sample, we report results for the benchmark models and for the three best-performing macroeconomic specifications from Panel B of Table VI (i.e., PCESVx, USSERV, and HOUST). We focus on two performance measures: the number of statistically significant anomalies and the average percentage reduction in CAPM alpha.

[10]The set of OSAP portfolios is identical to that used for latent factor extraction (Section 4.1). The tests summarized in Table VII, however, are based on return differences between the extreme quintile portfolios for each characteristic.

Across the alternative samples, the two-factor macroeconomic models continue to perform strongly relative to the standard benchmarks. With one minor exception, they yield fewer remaining significant anomalies and larger average CAPM alpha reductions than do the benchmark models. The only deviation arises in the value-weighted GFD tercile sample, where the HOUST specification slightly underperforms the Fama-French (2016) six-factor model and Hou-Xue-Zhang (2015) *q*-factor model in terms of average alpha reduction.

4.4.4 Anomaly Categories

In Table VIII, we summarize multifactor model performance by anomaly category. We focus on the five benchmark models and the three best-performing specifications from Table VI (i.e., the two-factor models with the PCESVx, USSERV, and HOUST factors). Panel A reports the number of statistically significant anomalies for each model-category combination, and Panel B reports the average CAPM alpha reduction. The results connect to a prior literature that focuses on the explanatory power of individual macroeconomic risks for specific anomalies. Several studies, for example, evaluate whether macroeconomic factors from the Chen, Roll, and Ross (1986) model account for the momentum anomaly (see, e.g., Griffin, Ji, and Martin, 2003; Liu and Zhang, 2008; Cooper, Mitrache, and Priestley, 2022).

All three macroeconomic factors perform strongly in resolving momentum anomalies. The two-factor PCESVx model reduces the average alpha across the seven momentum anomalies by 95.1%, with only one alpha remaining statistically significant. The corresponding reductions for the USSERV and HOUST models are also economically large, at 90.8% and 81.9%, respectively. Moreover, on both performance metrics, each macroeconomic specification matches or outperforms every benchmark model, including the Carhart (1997) four-factor model explicitly designed to capture momentum. These findings are broadly consistent with the evidence in Liu and Zhang (2008) and Cooper, Mitrache, and Priestley (2022) on the macroeconomic underpinnings of momentum strategies.

The two-factor USSERV and HOUST models resolve all 12 anomalies in the value category. The HOUST model's average alpha reduction of 98.3% exceeds that of all leading asset pricing models, including the two Fama-French models with an explicit value factor (*HML*). The macroeconomic models also perform well in explaining investment- and profitability-related anomalies. For example, the HOUST model reduces the average alpha of investment anomalies by 65.6% and resolves 21 of the 30 anomalies in this category. The two-factor model with the PCESVx factor reduces the average alpha of profitability anomalies by 33.7% and resolves more than half of these anomalies. The macroeconomic models slightly underperform the Fama-French (2016) and Hou-Xue-Zhang (2015) models based on average CAPM alpha reduction within the profitability category.

None of the two-factor models performs well in explaining intangibles anomalies, which include a relatively diverse group of strategies related to return correlation, debt issuance, change in long-term investment, and return seasonality. Across the eight CAPM anomalies in this group, the maximum average alpha reduction among the two-factor models is 28.2% (HOUST model). Under all three macroeconomic models, four of the eight anomalies remain statistically significant. The multifactor benchmark models fare no better, with the Fama-French (2016) model achieving the highest average alpha reduction among benchmarks at just 26.4%.

The three macroeconomic factors explain a substantial share of the abnormal returns for anomalies linked to trading frictions. For example, the HOUST model reduces the average alpha of the 20 anomalies by 81.3%, and just two of these anomalies exhibit positive and statistically significant two-factor alphas. The strong performance within the trading frictions category is noteworthy, as most anomalies in this group are based on liquidity or short-term market movements, and macroeconomic factors are often thought to be less relevant for such strategies in comparison with those based on predictors that evolve at business cycle frequencies.

4.5 Macroeconomic Explanations of Factor Momentum

As a final empirical application, we examine whether macroeconomic factors help explain the performance of factor momentum strategies, which have gained attention in recent literature (Ehsani and Linnainmaa, 2022; Arnott, Kalesnik, and Linnainmaa, 2023). Factor momentum refers to the tendency for a continuation of strong performance for asset pricing factors that have performed well in recent periods, and this phenomenon is known to be distinct from both individual stock momentum (Jegadeesh and Titman, 1993) and industry momentum (Moskowitz and Grinblatt, 1999).

Several prior studies explore the macroeconomic drivers of individual stock momentum profits (e.g., Griffin, Ji, and Martin, 2003; Liu and Zhang, 2008; Adrian, Etula, and Muir, 2014; Maio and Philip, 2018; Cooper, Mitrache, and Priestley, 2022), and our results in Table VIII contribute further evidence of this link. By contrast, relatively little is known about the macroeconomic drivers of factor momentum, making an analysis of these strategies a natural extension of our analyses in Section 4.4.4.

We consider two factor momentum trading strategies: a time-series factor momentum strategy following Ehsani and Linnainmaa (2022) and a cross-sectional factor momentum strategy following Arnott, Kalesnik, and Linnainmaa (2023). The underlying assets for the factor momentum portfolios are the excess returns for 141 long-short anomaly portfolios. This set comprises the 149 long-short anomaly portfolios from GFD described in Section 3.4, excluding the eight classified in the momentum category. At the start of each quarter, we calculate the average excess return for each of the 141 anomaly portfolios over the previous four quarters. The time-series strategy takes a long (short) position in anomalies with positive (negative) average returns, whereas the cross-sectional strategy takes a long (short) position in anomalies with above-median (below-median) average returns. The anomaly portfolios are equally weighted within each strategy.

We report the performance of the two factor momentum strategies in Table IX. Because the factor momentum portfolios require a four-quarter formation period, the sample period spans 1971–2024. As a preliminary step, we confirm that the factor momentum effects documented in Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023) are also present for our sample period, underlying anomaly strategies, and strategy formation choices.[11] The time-series factor momentum strategy (Panel A) earns an average return of 1.67% per year and a CAPM alpha of 2.06%. Both estimates are statistically significant at the 1% level. The cross-sectional strategy performs slightly weaker, but its average return of 1.11% and CAPM alpha of 1.40% are both economically and statistically significant. The CAPM R^2s for the two strategies are below 3%, suggesting that static exposure to the market factor explains little of the time-series variability in strategy returns.

In the last three columns of Table IX, we summarize the performance of models with macroeconomic factors. We again consider the three best-performing specifications from Table VI: the two-factor models with the PCESVx, USSERV, and HOUST factors. All three models offer compelling explanations for the factor momentum effects in average returns. In Panel A, for example, augmenting the CAPM with the PCESVx factor reduces the abnormal return of the time-series factor momentum strategy from 2.06% to −0.43% per year. Similarly, the abnormal returns under the two-factor USSERV and HOUST models are 0.46% and 0.40%, respectively. In Panel B, the CAPM alpha for the cross-sectional factor momentum strategy of 1.40% is reduced to between −0.90% and 0.10% across the macroeconomic models. Each of the two-factor macroeconomic model alpha estimates is statistically insignificant. Moreover, the estimated loadings for the factor momentum strategies on the three macroeconomic factors are uniformly positive (and statistically significant for the PCESVx and USSERV factors). These results reveal a strong association between macroeconomic risks and factor momentum returns.

[11] Ehsani and Linnainmaa (2022) evaluate time-series and cross-sectional factor momentum strategies with a 12-month formation period and a one-month holding period. Arnott, Kalesnik, and Linnainmaa (2023) consider cross-sectional momentum strategies with a one-month formation period and a one-month holding period. The strategies in these studies are based on a smaller set of underlying anomaly portfolios relative to our set of 141. Because our anomaly returns are quarterly, we specify a quarterly holding period for our factor momentum strategies. Ehsani and Linnainmaa (2022) show in their internet appendix that time-series and cross-sectional factor momentum strategies based on 12-month formation periods and quarterly holding periods earn economically large and statistically significant average returns.

5 Conclusion

We provide a comprehensive evaluation of the underlying macroeconomic risks in the cross section of stock returns. Our empirical framework combines Giglio and Xiu's (2021) three-pass approach for macroeconomic risk premium estimation and mimicking portfolio construction with Lettau and Pelger's (2020a,b) RP-PCA approach for latent factor extraction. Together, these approaches leverage information from a large panel of equity portfolios while mitigating omitted variable bias and efficiently identifying latent factors that capture both time-series and cross-sectional properties of returns. Whereas most prior studies examine the macroeconomic drivers of individual anomalies or risk premia within a narrow subset of cross-sectional trading strategies, we assess whether macroeconomic risks account for broad patterns in the anomaly zoo.

The results reveal a deeper link between macroeconomic risks and the cross section of stock returns than has been documented in other asset markets using similar methods (e.g., Nucera, Sarno, and Zinna, 2024), a link that would likely remain obscured under narrower empirical designs. Based on a model with six latent factors, 46 of the 192 candidate macroeconomic variables are associated with statistically significant risk premia, and 12 remain significant after adjusting for multiple testing. A small set of interpretable macroeconomic factors linked to personal consumption expenditures, employment, and housing emerges as particularly powerful in explaining the dispersion in average returns. Models that incorporate mimicking portfolios for these variables match or exceed the performance of leading characteristic-based multifactor benchmarks in reconciling asset pricing anomalies. Taken together, these findings indicate that macroeconomic risks play a central role in shaping the cross section of equity returns.

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Table I: Tests for the Optimal Number of Latent Factors

The table reports the optimal number of latent factors extracted from a cross section of 865 equity portfolios. We consider latent factor estimation using Lettau and Pelger's (2020a,b) RP-PCA approach with penalty parameters $\omega = 10$ and $\omega = -1$. The $\omega = -1$ case corresponds to standard PCA estimation. For each estimation approach, the table shows the number of factors suggested by the Onatski (2010) and Giglio and Xiu (2021) tests. The Giglio and Xiu (2021) tests are based on the small ($P_{GX} = 0.25$), medium ($P_{GX} = 0.50$), and large ($P_{GX} = 0.75$) overfitting penalty values.

		Factor estimation method	
Test	Overfitting penalty	RP-PCA ($\omega = 10$)	PCA ($\omega = -1$)
Onatski (2010)	N/A	3	3
Giglio and Xiu (2021)	Small ($P_{GX} = 0.25$)	6	7
Giglio and Xiu (2021)	Medium ($P_{GX} = 0.50$)	4	3
Giglio and Xiu (2021)	Large ($P_{GX} = 0.75$)	4	3

Table II: Properties of the Latent Factors

The table reports properties of the six latent factors extracted from a cross section of 865 equity portfolios. We consider latent factor estimation using Lettau and Pelger's (2020a,b) RP-PCA approach with penalty parameters $\omega = 10$ and $\omega = -1$. The $\omega = -1$ case corresponds to standard PCA estimation. For each latent factor, the table reports the annualized mean excess return, the annualized standard deviation of excess return, and the annualized Sharpe ratio. In each estimation approach, the factors are sequentially orthogonalized using the Gram-Schmidt method and the factors are scaled so that the standard deviation of the first factor is equal to that of the market factor.

	RP-PCA estimation ($\omega = 10$)			PCA estimation ($\omega = -1$)		
Factor (k)	Mean (%)	StDev (%)	Sharpe ratio	Mean (%)	StDev (%)	Sharpe ratio
1	7.64	17.63	0.43	7.36	17.63	0.42
2	2.22	3.10	0.71	0.49	3.80	0.13
3	1.29	3.52	0.37	1.61	3.12	0.52
4	1.70	1.41	1.20	0.55	1.70	0.32
5	0.87	1.55	0.56	0.60	1.51	0.40
6	0.61	1.40	0.43	0.33	1.41	0.23

Table III: Spanning Regressions for Latent RP-PCA Factors

The table reports results from spanning regressions of latent factors on the market factor (Panel A), the six Fama-French (2016) factors (Panel B), and the four Hou-Xue-Zhang (2015) factors (Panel C). The six latent factors are extracted from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with penalty parameter $\omega = 10$. For each spanning regression, the table reports the annualized alpha, the factor loadings, and the regression R^2 value. The numbers in parentheses are Newey-West (1987) t-statistics based on a lag length equal to four. For the alpha and factor loading estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a two-tailed test.

Parameter	F_1	F_2	F_3	F_4	F_5	F_6
Panel A: CAPM Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	0.12	2.08***	1.54**	1.69***	0.88***	0.58***
	(0.19)	(4.60)	(2.42)	(8.83)	(3.29)	(2.70)
MKT loading, $\widehat{\beta}_k$	0.98***	0.02	−0.03	0.00	0.00	0.00
R^2 (%)	95.78	1.06	2.62	0.01	0.03	0.20
Panel B: Fama-French (2016) Six-Factor Model Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	−0.03	0.21	0.08	1.10***	0.47**	0.62***
	(−0.14)	(1.17)	(0.58)	(8.81)	(2.15)	(3.41)
Factor loadings:						
MKT	0.91***	0.12***	−0.03***	0.00	0.02***	0.02***
SMB	0.29***	−0.17***	0.20***	0.07***	−0.02**	−0.05***
HML	0.04***	0.07***	0.13***	−0.02***	0.02**	0.03**
RMW	0.01	0.18***	0.10***	0.01	−0.06***	−0.05***
CMA	0.06***	0.08***	0.09***	0.00	0.06***	0.02
UMD	−0.04***	0.04***	0.00	0.08***	0.03***	−0.01
R^2 (%)	99.57	82.39	92.00	77.42	36.02	27.19
Panel C: Hou-Xue-Zhang (2015) q-Factor Model Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	0.02	0.05	0.08	1.28***	0.70**	0.70***
	(0.10)	(0.17)	(0.20)	(4.76)	(2.29)	(3.18)
Factor loadings:						
MKT	0.90***	0.11***	−0.05***	−0.01	0.01**	0.02***
ME	0.29***	−0.14***	0.22***	0.05***	−0.03**	−0.05***
ROE	−0.07***	0.16***	0.01	0.07***	−0.03***	−0.05***
IA	0.07***	0.17***	0.22***	−0.02	0.08***	0.06***
R^2 (%)	99.37	71.66	73.42	25.55	19.11	23.60

Table IV: Macroeconomic Factors with Statistically Significant Risk Premia

The table reports estimates of the risk premia for selected macroeconomic factors using the augmented three-pass approach of Giglio and Xiu (2021). The table focuses on macroeconomic factors with statistically significant risk premia. The latent factors are estimated from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the number of latent factors $K = 6$ and the RP-PCA penalty parameter $\omega = 10$. For each macroeconomic variable, the table reports the risk premium estimate, the corresponding asymptotic standard error and t-statistic, the R^2 value obtained from projecting the macroeconomic variable onto the K latent factors, the projected factor's annualized Sharpe ratio, and the p-value from a test of the null hypothesis that the factor is weak. The final column reports the Benjamini-Hochberg (1995) adjusted p-value for the risk premium estimate, which accounts for multiple testing across the full set of macroeconomic variables. For the risk premium estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a two-tailed test. The panels of the table are grouped by macroeconomic variable category.

	Three-pass estimation					Weak factor	FDR analysis
Variable	$\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	p-value	p_{BH}-value
Panel A: NIPA (4/22)							
PCESVx	0.554***	0.213	2.60	4.65	1.28	0.13	0.18
PRFIx	0.451**	0.205	2.20	6.83	0.86	0.01	0.30
IMPGSC1	0.418**	0.200	2.09	5.63	0.88	0.03	0.35
PCECC96	0.451*	0.235	1.92	2.77	1.36	0.14	0.37
Panel B: Industrial Production (1/16)							
IPNCONGD	0.361*	0.190	1.90	6.15	0.73	0.04	0.37
Panel C: Employment and Unemployment (23/49)							
USPBS	0.576***	0.184	3.13	6.73	1.11	0.02	0.14
USSERV	0.393***	0.128	3.07	5.93	0.81	0.04	0.14
SRVPRD	0.368**	0.162	2.28	6.22	0.74	0.11	0.28
USTRADE	0.383**	0.173	2.22	4.56	0.90	0.17	0.30
HOANBS	0.429**	0.211	2.03	4.82	0.98	0.33	0.37
HOABS	0.421**	0.211	1.99	4.82	0.96	0.28	0.37
USFIRE	0.369**	0.187	1.98	3.42	1.00	0.37	0.37
LNS12032194	−0.380*	0.195	−1.94	4.68	−0.88	0.27	0.37
UEMP5TO14	−0.281*	0.146	−1.92	3.03	−0.81	0.45	0.37
LNS14000012	−0.309*	0.162	−1.91	2.24	−1.03	0.54	0.37
USCONS	0.370*	0.195	1.89	3.67	0.97	0.29	0.37
USINFO	0.381*	0.202	1.89	4.89	0.86	0.09	0.37
LNS13023621	−0.316*	0.173	−1.83	4.38	−0.75	0.34	0.38
AWHMAN	0.328*	0.181	1.81	1.88	1.20	0.56	0.38
HWIURATIOx	0.399*	0.225	1.77	2.96	1.16	0.42	0.38
CES0600000007	0.344*	0.195	1.77	1.73	1.31	0.36	0.38
USEHS	0.254*	0.145	1.75	5.13	0.56	0.68	0.38
USTPU	0.347*	0.199	1.75	5.53	0.74	0.13	0.38
CE16OV	0.318*	0.183	1.74	5.29	0.69	0.21	0.38
LNS14000025	−0.336*	0.194	−1.73	4.88	−0.76	0.40	0.38
PAYEMS	0.323*	0.191	1.69	6.20	0.65	0.21	0.41
USPRIV	0.324*	0.196	1.66	6.04	0.66	0.28	0.41
HWIx	0.453*	0.274	1.65	6.13	0.92	0.42	0.41

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Table IV (Continued)

Variable	$\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	Weak factor p-value	FDR analysis p_{BH}-value
	Three-pass estimation						
Panel D: Housing (11/11)							
HOUSTMW	0.643***	0.190	3.39	7.61	1.17	0.00	0.13
HOUST	0.585***	0.200	2.92	7.22	1.09	0.01	0.17
PERMITS	0.615***	0.221	2.78	7.30	1.14	0.02	0.17
HOUSTNE	0.527***	0.200	2.63	5.87	1.09	0.05	0.18
HOUSTS	0.552***	0.211	2.62	6.06	1.12	0.07	0.18
PERMIT	0.514**	0.201	2.56	7.11	0.96	0.01	0.18
PERMITW	0.517**	0.207	2.50	5.97	1.06	0.04	0.20
HOUST5F	0.563**	0.238	2.36	3.86	1.43	0.33	0.26
PERMITNE	0.428**	0.182	2.35	8.03	0.75	0.05	0.26
HOUSTW	0.449**	0.198	2.27	5.60	0.95	0.04	0.28
PERMITMW	0.353*	0.188	1.87	7.28	0.65	0.00	0.37
Panel E: Inventories, Orders, and Sales (0/8)							
< None >							
Panel F: Prices (3/47)							
CUSR0000SAD	−0.548***	0.194	−2.83	5.53	−1.17	0.01	0.17
DMOTRG3Q086SBEA	−0.377**	0.190	−1.98	2.38	−1.22	0.14	0.37
WPU0531	0.344*	0.199	1.73	7.88	0.61	0.00	0.38
Panel G: Earnings and Productivity (2/11)							
COMPRNFB	−0.354*	0.205	−1.73	10.40	−0.55	0.01	0.38
RCPHBS	−0.339*	0.203	−1.67	10.22	−0.53	0.01	0.41
Panel H: Money and Credit (1/14)							
DTCOLNVHFNM	−0.506**	0.238	−2.13	4.20	−1.24	0.04	0.34
Panel I: Consumer Sentiment (0/1)							
< None >							
Panel J: Non-Household Balance Sheets (1/13)							
TNWMVBSNNCBx	0.662***	0.252	2.62	28.85	0.62	0.00	0.18

Table V: Long-Short Portfolios with Statistically Significant CAPM Alphas

The table reports average returns and parameter estimates from CAPM regressions for long-short tercile portfolios sorted on various firm characteristics. The average returns and alphas are reported in percent per year. The t-statistics for the average returns and CAPM regression parameters are constructed following the approach in Newey and West (1987) based on a lag length equal to four. The table includes results for the 104 of the 149 long-short portfolios with statistically significant CAPM alphas at the 5% level. For the average return and alpha estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a one-tailed test. The panels of the table are grouped by anomaly variable category.

	Average returns		CAPM regressions				
Anomaly	$\overline{R}_i$ (%)	$t(\overline{R}_i)$	$\widehat{\alpha}_i^C$ (%)	$t(\widehat{\alpha}_i^C)$	$\widehat{\beta}_i$ (%)	$t(\widehat{\beta}_i)$	R^2 (%)
Panel A: Momentum							
prc_highprc_252d	2.44	1.01	6.90***	3.22	−0.58	−6.78	33.39
resff3_12_1	6.82***	5.04	7.42***	5.50	−0.08	−1.59	2.66
resff3_6_1	3.11***	2.84	3.91***	3.53	−0.10	−2.36	6.09
ret_12_1	6.26***	3.20	7.78***	4.32	−0.20	−2.20	5.23
ret_6_1	2.83*	1.64	4.03***	2.50	−0.16	−2.36	4.32
ret_9_1	4.74***	2.59	6.31***	3.84	−0.20	−2.74	6.45
seas_1_1na	3.62**	1.87	4.91***	2.80	−0.17	−1.99	3.82
Panel B: Value							
be_me	3.12*	1.41	4.38**	1.96	−0.16	−1.87	4.25
bev_mev	2.78	1.18	4.08**	1.67	−0.17	−1.72	3.97
chcsho_12m	4.34***	2.76	6.19***	3.69	−0.24	−3.61	17.30
div12m_me	2.48	1.10	6.38***	3.08	−0.51	−6.98	32.90
ebitda_mev	6.96***	2.60	8.85***	3.14	−0.25	−2.32	7.64
eq_dur	4.27**	1.86	6.12***	2.54	−0.24	−2.84	9.48
eqnpo_12m	4.32**	2.20	7.66***	4.16	−0.43	−6.91	34.10
fcf_me	6.11***	3.49	7.18***	3.71	−0.14	−2.25	5.35
ival_me	4.50***	2.52	4.98***	2.62	−0.06	−0.91	0.98
ni_me	4.98**	1.85	7.79***	2.87	−0.37	−3.66	16.31
ocf_me	6.93***	2.93	9.07***	3.60	−0.28	−2.76	11.23
sale_me	5.54**	2.26	5.72**	2.09	−0.02	−0.22	0.08
Panel C: Investment							
aliq_at	2.01	1.00	5.51***	2.88	−0.46	−5.71	32.88
at_gr1	3.76**	2.18	5.87***	3.20	−0.28	−3.83	19.13
be_gr1a	2.90**	1.79	4.54***	2.50	−0.21	−3.09	11.54
capex_abn	2.70***	4.23	2.70***	4.03	0.00	−0.03	0.00
capx_gr1	4.29***	3.53	5.60***	3.89	−0.17	−2.92	14.09
capx_gr2	3.80***	3.39	5.31***	4.35	−0.20	−3.89	16.82
capx_gr3	3.22***	2.82	4.72***	3.93	−0.19	−4.52	17.15
coa_gr1a	2.94***	2.41	4.88***	3.98	−0.25	−5.15	24.38
cowc_gr1a	3.91***	5.20	4.71***	5.30	−0.10	−3.06	11.15
debt_gr3	2.83***	3.79	3.57***	5.10	−0.10	−4.93	13.14
emp_gr1	2.90**	1.93	5.00***	3.23	−0.27	−4.37	20.74
fnl_gr1a	3.28***	4.95	3.62***	5.90	−0.04	−2.52	3.65
inv_gr1	4.75***	4.77	5.94***	5.42	−0.16	−3.75	14.42
inv_gr1a	3.65***	4.28	4.81***	5.10	−0.15	−4.21	15.12
lnoa_gr1a	4.40***	3.94	5.40***	4.42	−0.13	−3.08	9.29
mispricing_mgmt	6.36***	4.12	8.54***	5.32	−0.28	−5.08	25.63

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Table V (Continued)

Anomaly	Average returns $\overline{R}_i$ (%)	$t(\overline{R}_i)$	CAPM regressions $\widehat{\alpha}_i^C$ (%)	$t(\widehat{\alpha}_i^C)$	$\widehat{\beta}_i$ (%)	$t(\widehat{\beta}_i)$	R^2 (%)
Panel C: Investment (Continued)							
ncoa_gr1a	4.88***	4.18	5.59***	4.25	−0.09	−2.08	5.30
nfna_gr1a	3.26***	5.42	3.58***	6.24	−0.04	−2.76	3.84
nncoa_gr1a	5.02***	4.50	5.89***	4.77	−0.11	−2.65	7.91
noa_at	5.70***	5.45	5.68***	5.07	0.00	0.07	0.00
noa_gr1a	6.11***	4.66	7.88***	5.48	−0.23	−4.66	23.07
oaccruals_at	4.95***	4.35	5.09***	3.79	−0.02	−0.30	0.18
oaccruals_ni	4.32***	5.59	4.74***	5.31	−0.06	−1.58	3.25
ppeinv_gr1a	4.69***	3.36	6.18***	4.05	−0.19	−3.65	14.91
ret_60_12	2.08*	1.38	2.70**	1.70	−0.08	−1.16	1.58
sale_gr1	2.76**	1.70	4.72***	2.77	−0.25	−3.41	14.93
sale_gr3	2.04*	1.57	3.98***	3.34	−0.25	−5.01	20.77
seas_2_5na	3.04**	1.82	5.03***	2.98	−0.26	−3.50	14.10
taccruals_at	2.13**	2.01	2.18**	1.75	−0.01	−0.12	0.02
taccruals_ni	1.69**	2.21	2.11**	2.25	−0.05	−1.56	3.48
Panel D: Profitability							
cop_at	6.88***	7.08	7.53***	7.96	−0.08	−2.89	5.06
cop_atl1	5.67***	5.82	5.65***	5.69	0.00	0.07	0.00
dsale_dinv	2.74***	4.04	2.95***	4.15	−0.03	−1.16	1.28
ebit_bev	4.14***	2.72	4.82***	2.86	−0.09	−1.34	2.74
ebit_sale	0.97	0.51	3.70**	1.95	−0.35	−5.49	27.45
f_score	3.47***	2.69	5.49***	4.82	−0.26	−5.37	26.86
gp_at	3.43***	2.82	2.51**	1.91	0.12	2.75	5.34
mispricing_perf	5.09***	3.41	6.14***	4.24	−0.14	−2.31	5.41
ni_be	2.83**	1.67	4.02**	2.14	−0.15	−1.96	6.42
niq_at	3.00**	1.82	4.09**	2.30	−0.14	−2.10	5.53
niq_at_chg1	2.61***	2.92	3.06***	3.55	−0.06	−1.54	2.84
niq_be	3.85***	2.40	4.99***	2.90	−0.15	−2.03	6.26
niq_be_chg1	2.91***	3.25	3.79***	4.95	−0.12	−3.01	9.94
niq_su	2.35***	3.49	2.72***	4.37	−0.05	−1.74	2.40
o_score	2.46**	2.06	3.29***	2.86	−0.11	−2.58	6.32
ocf_at	6.27***	4.61	8.16***	7.04	−0.25	−6.56	24.07
ocf_at_chg1	2.19***	3.25	2.21***	2.87	0.00	−0.10	0.01
op_at	3.96***	3.06	4.27***	3.16	−0.04	−0.99	0.66
ope_be	4.22***	2.70	5.04***	2.81	−0.11	−1.53	3.76
ope_bel1	2.37**	1.98	2.40**	1.82	0.00	−0.07	0.01
qmj	3.10***	2.81	4.31***	4.31	−0.16	−3.48	11.44
qmj_growth	2.45***	3.27	2.73***	3.67	−0.04	−1.16	1.04
qmj_prof	4.71***	4.01	5.53***	4.73	−0.11	−2.52	5.64
qmj_safety	1.00	0.78	2.69**	2.14	−0.22	−3.84	19.90
ret_12_7	6.61***	3.48	7.07***	3.76	−0.06	−0.75	0.63
sale_bev	4.17***	4.02	2.84***	2.67	0.17	5.09	14.70
seas_1_1an	2.94***	2.39	2.49**	1.92	0.06	1.37	1.20

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Table V (Continued)

	Average returns		CAPM regressions				
Anomaly	$\overline{R}_i$ (%)	$t(\overline{R}_i)$	$\widehat{\alpha}_i^C$ (%)	$t(\widehat{\alpha}_i^C)$	$\widehat{\beta}_i$ (%)	$t(\widehat{\beta}_i)$	R^2 (%)
Panel E: Intangibles							
corr_1260d	0.19	0.14	2.30**	1.80	−0.27	−5.77	25.93
dbnetis_at	2.64***	3.54	2.80***	3.32	−0.02	−0.74	0.52
lti_gr1a	0.70*	1.28	1.07**	1.76	−0.05	−1.78	4.54
seas_11_15an	2.50***	3.33	2.65***	3.71	−0.02	−0.78	0.42
seas_11_15na	1.54**	1.72	2.04***	2.37	−0.06	−2.39	3.13
seas_16_20an	3.15***	3.98	3.19***	3.65	0.00	−0.15	0.02
seas_2_5an	3.10***	2.63	2.62**	2.10	0.06	1.83	2.19
seas_6_10an	4.56***	5.70	4.25***	5.51	0.04	1.40	1.32
Panel J: Trading Frictions							
beta_60m	0.06	0.02	5.62***	2.80	−0.72	−9.59	51.68
beta_dimson_21d	0.24	0.15	3.56**	2.30	−0.43	−6.71	40.93
betabab_1260d	1.08	0.45	6.71***	3.60	−0.73	−10.35	54.06
betadown_252d	−0.25	−0.10	5.29**	2.31	−0.72	−7.42	48.50
ivol_capm_21d	3.70*	1.42	8.74***	3.64	−0.66	−7.19	40.02
ivol_capm_252d	2.62	0.88	8.45***	3.20	−0.76	−7.48	41.04
ivol_ff3_21d	3.62*	1.42	8.50***	3.57	−0.64	−7.02	39.12
ivol_hxz4_21d	3.54*	1.40	8.37***	3.55	−0.63	−7.02	38.80
ocfq_saleq_std	1.56	1.10	3.19**	2.30	−0.21	−3.59	15.58
rd_me	5.07***	3.36	3.63**	2.26	0.19	3.11	8.21
ret_1_0	4.62***	3.33	2.93**	2.13	0.22	5.65	12.22
rmax1_21d	4.16**	1.71	8.80***	3.87	−0.60	−6.84	41.88
rmax5_21d	4.99**	1.88	9.93***	4.08	−0.64	−7.18	41.55
rmax5_rvol_21d	4.55***	5.72	4.37***	5.36	0.02	1.22	0.54
rskew_21d	0.50	0.86	1.20**	1.91	−0.09	−3.73	13.91
rvol_21d	3.68*	1.33	9.38***	3.72	−0.74	−7.72	45.19
seas_6_10na	3.64***	3.11	5.32***	4.74	−0.22	−5.41	21.68
turnover_126d	0.79	0.40	4.70***	2.86	−0.51	−7.71	43.44
zero_trades_126d	1.13	0.59	4.70***	2.90	−0.47	−6.75	39.96
zero_trades_252d	1.52	0.81	5.00***	3.02	−0.45	−6.29	38.49

Table VI: Asset Pricing Model Performance

The table summarizes the performance of various multifactor models in explaining the average returns for the 104 of the 149 long-short capped-value-weighted tercile portfolios with statistically significant CAPM alphas at the 5% level. Panel A shows results for five benchmark models, and Panel B shows results for two-factor models that include the market factor and the mimicking portfolio for the indicated macroeconomic factor. The benchmark models in Panel A are the CAPM, the Carhart (1997) four-factor model, the Fama-French (2015) five-factor model, the Fama-French (2016) six-factor model, and the Hou-Xue-Zhang (2015) q-factor model. The macroeconomic factors considered in Panel B are those with risk premia estimated using the augmented three-pass approach of Giglio and Xiu (2021) that are statistically significant and survive multiple testing correction. For each model, the table reports (i) the average absolute alpha (in percent per year), (ii) the average alpha (in percent per year), (iii) the average percentage reduction in the CAPM alpha, and (iv) the number of alpha estimates that are statistically significant at the 5% level using a one-tailed test across the 104 long-short portfolios.

Model	Category	$\mathbb{A}[\lvert\widehat{\alpha}_i\rvert]$ (%)	$\mathbb{A}[\widehat{\alpha}_i]$ (%)	Average $\widehat{\alpha}_i^C$ reduction (%)	Significant anomalies
		Panel A: Benchmark Models			
CAPM	None	5.00	5.00	0.0	104
C4 (Carhart, 1997)	None	3.28	3.22	31.7	88
FF5 (Fama and French, 2015)	None	2.52	2.21	45.8	58
FF6 (Fama and French, 2016)	None	2.10	1.78	54.7	56
q4 (Hou, Xue, and Zhang, 2015)	None	2.12	1.58	55.5	46
		Panel B: Two-Factor Models with Macroeconomic Factors			
PCESVx	NIPA	2.45	0.92	58.7	34
USPBS	Employment	2.61	1.88	48.5	50
USSERV	Employment	2.59	0.81	57.7	36
HOUST	Housing	2.81	0.21	61.4	33
PERMIT	Housing	3.04	2.57	40.0	59
HOUSTMW	Housing	2.41	1.20	56.8	40
HOUSTNE	Housing	2.81	1.53	48.2	46
HOUSTS	Housing	2.54	1.61	52.2	41
PERMITS	Housing	2.96	2.71	38.6	52
PERMITW	Housing	2.89	1.85	45.8	47
CUSR0000SAD	Prices	2.60	1.78	49.1	44
TNWMVBSNNCBx	NHBS	4.32	4.32	11.7	96

Table VII: Asset Pricing Model Performance for Alternative Anomaly Portfolios

The table summarizes the performance of various multifactor models in explaining the average returns for alternative sets of long-short anomaly portfolios with statistically significant CAPM alphas at the 5% level. The test assets are 149 long-short anomaly tercile portfolios from the Global Factor Data (GFD) website that are capped value weighted (CVW), value weighted (VW), or equal weighted (EW), or 110 long-short anomaly quintile portfolios from the Open Source Asset Pricing (OSAP) website that are value weighted. Panel A shows results for five benchmark models, and Panel B shows results for two-factor models that include the market factor and the mimicking portfolio for the indicated macroeconomic factor. The macroeconomic models considered are the best performing models from Table VI. For each combination of model and test assets, the table reports the number of alpha estimates that are statistically significant at the 5% level using a one-tailed test and the average percentage reduction in the CAPM alpha across the long-short portfolios with significantly positive CAPM alphas.

		Significant anomalies				Average $\widehat{\alpha}_i^C$ reduction (%)			
Model	Category	GFD CVW Terciles ($N = 149$)	GFD VW Terciles ($N = 149$)	GFD EW Terciles ($N = 149$)	OSAP VW Quintiles ($N = 110$)	GFD CVW Terciles ($N = 149$)	GFD VW Terciles ($N = 149$)	GFD EW Terciles ($N = 149$)	OSAP VW Quintiles ($N = 110$)
Panel A: Benchmark Models									
CAPM	None	104	87	116	64	0.0	0.0	0.0	0.0
C4	None	88	57	101	38	31.7	34.5	25.8	40.7
FF5	None	58	42	95	32	45.8	46.9	35.3	41.6
FF6	None	56	34	85	29	54.7	57.8	44.0	54.2
$q4$	None	46	31	72	25	55.5	56.5	46.1	51.5
Panel B: Two-Factor Models with Individual Macroeconomic Factors									
PCESVx	NIPA	34	23	63	15	58.7	61.8	49.4	64.8
USSERV	Employment	36	27	67	14	57.7	59.6	48.3	60.8
HOUST	Housing	33	22	51	17	61.4	55.7	55.6	62.7

Table VIII: Asset Pricing Model Performance by Anomaly Group

The table summarizes the performance of various multifactor models in explaining the average returns for the 104 of the 149 long-short capped-value-weighted tercile portfolios with statistically significant CAPM alphas at the 5% level. The tables focuses on model performance by anomaly group. The first section in each panel presents results for the five benchmark models. The subsequent section presents results for models that include the market factor and the mimicking portfolio for the indicated macroeconomic factor. The macroeconomic models considered are the best performing models from Table VI. For each model and anomaly category, Panel A reports the number of alpha estimates that are statistically significant at the 5% level using a one-tailed test, and Panel B reports the average percentage reduction in the CAPM alpha across the long-short portfolios with significantly positive CAPM alphas.

	Benchmarks					Two-factor models		
Anomaly group	CAPM	C4	FF5	FF6	$q4$	PCESVx	USSERV	HOUST
Panel A: Significant Anomalies								
Momentum	7	1	6	2	1	1	1	1
Value	12	12	0	6	1	1	0	0
Investment	30	29	20	21	19	12	14	9
Profitability	27	25	22	17	16	13	14	17
Intangibles	8	5	5	5	5	4	4	4
Trading frictions	20	16	5	5	4	3	3	2
Panel B: Average $\widehat{\alpha}_i^C$ Reduction (%)								
Momentum	0.0	86.4	10.2	87.5	65.6	95.1	90.8	81.9
Value	0.0	34.2	91.4	73.9	86.5	76.0	84.6	98.3
Investment	0.0	34.0	49.6	46.7	45.3	65.8	58.3	65.6
Profitability	0.0	12.5	21.2	42.9	48.7	33.7	37.8	29.9
Intangibles	0.0	18.9	14.5	26.4	18.1	23.4	17.0	28.2
Trading frictions	0.0	38.8	71.2	71.1	73.0	72.8	72.3	81.3

Table IX: Factor Momentum Strategies

The table summarizes the performance of a time-series factor momentum strategy (Panel A) and a cross-sectional factor momentum strategy (Panel B). The factor momentum strategies are constructed based on the lagged 12-month performance of 141 non-momentum long-short anomaly portfolios. For each factor momentum strategy, the table reports the annualized average return, parameter estimates from time-series CAPM regressions, and parameter estimates from two-factor model regressions that include the market factor and either the PCESVx factor, the USSERV factor, or the HOUST factor. For each regression, the table reports the annualized alpha, the factor loadings, and the regression R^2 value. The numbers in parentheses are Newey-West (1987) t-statistics based on a lag length equal to four. For the average return, alpha, and factor loading estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a two-tailed test.

	Benchmarks		Two-factor models		
Parameter	Average return	CAPM	PCESVx	USSERV	HOUST
Panel A: Time-Series Factor Momentum					
Intercept, $\widehat{\alpha}_i$ (%)	1.67***	2.06***	−0.43	0.46	0.40
	(3.06)	(3.47)	(−0.80)	(0.65)	(0.43)
Market factor (MKT) loading, $\widehat{\beta}_i$		−0.05	−0.04	0.00	−0.17*
		(−1.57)	(−1.34)	(−0.15)	(−1.71)
Macro factor ($\widehat{G}_l^A$) loading, $\widehat{m}_i$			0.17***	0.14*	0.21
			(3.61)	(1.90)	(1.63)
R^2 (%)		2.94	15.85	9.50	8.36
Panel B: Cross-Sectional Factor Momentum					
Intercept, $\widehat{\alpha}_i$ (%)	1.11**	1.40***	−0.90	−0.04	0.10
	(2.22)	(2.71)	(−1.59)	(−0.05)	(0.10)
Market factor (MKT) loading, $\widehat{\beta}_i$		−0.04	−0.02	0.01	−0.13
		(−1.23)	(−0.94)	(0.26)	(−1.42)
Macro factor ($\widehat{G}_l^A$) loading, $\widehat{m}_i$			0.16***	0.13*	0.17
			(3.60)	(1.81)	(1.38)
R^2 (%)		1.72	13.73	7.49	5.34

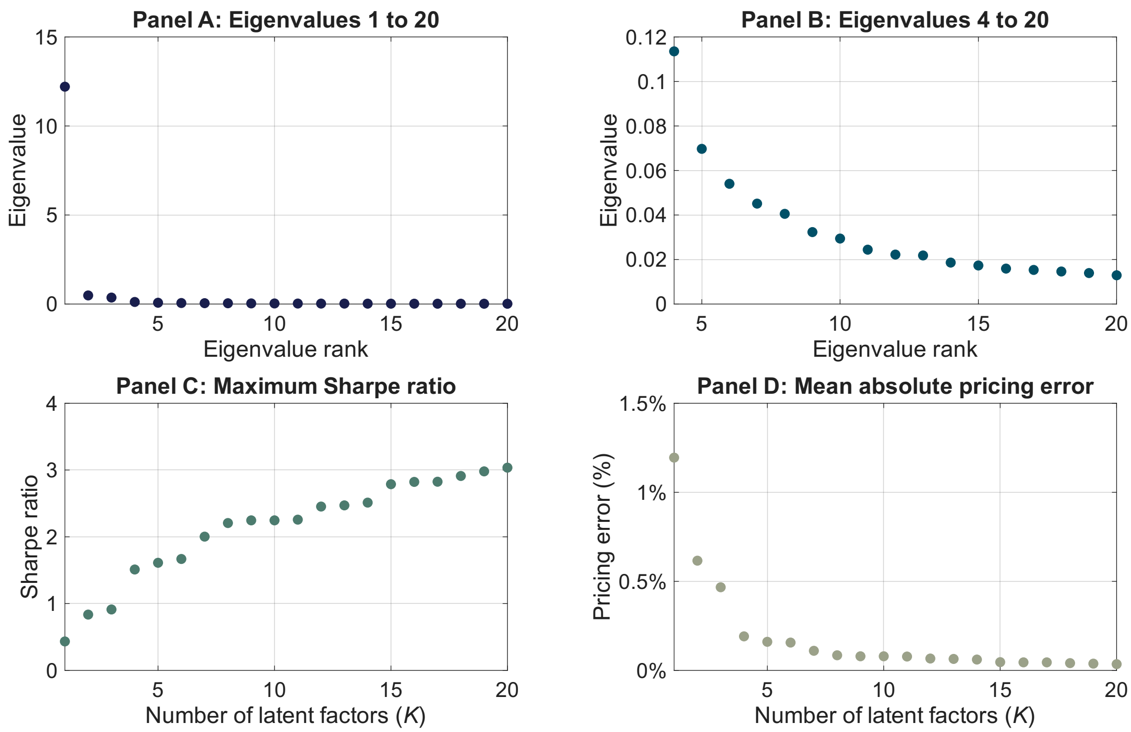

Figure 1. RP-PCA Model Diagnostics for Selecting the Number of Latent Factors. The figure shows model diagnostics from the first and second stages of the augmented Giglio and Xiu (2021) procedure applied to a cross section of 865 equity portfolios. We estimate models with up to 20 latent factors based on the RP-PCA method of Lettau and Pelger (2020a,b) with an RP-PCA penalty parameter $\omega = 10$. Panel A presents the largest twenty eigenvalues of the covariance matrix of excess returns for the 865 portfolios, and Panel B presents eigenvalues ranked between 4 and 20. For models of up to 20 factors, Panel C presents the implied Sharpe ratio of the tangency portfolio spanned by the linear combination of the K latent factors and Panel D presents the average absolute pricing error from the cross-sectional regression.

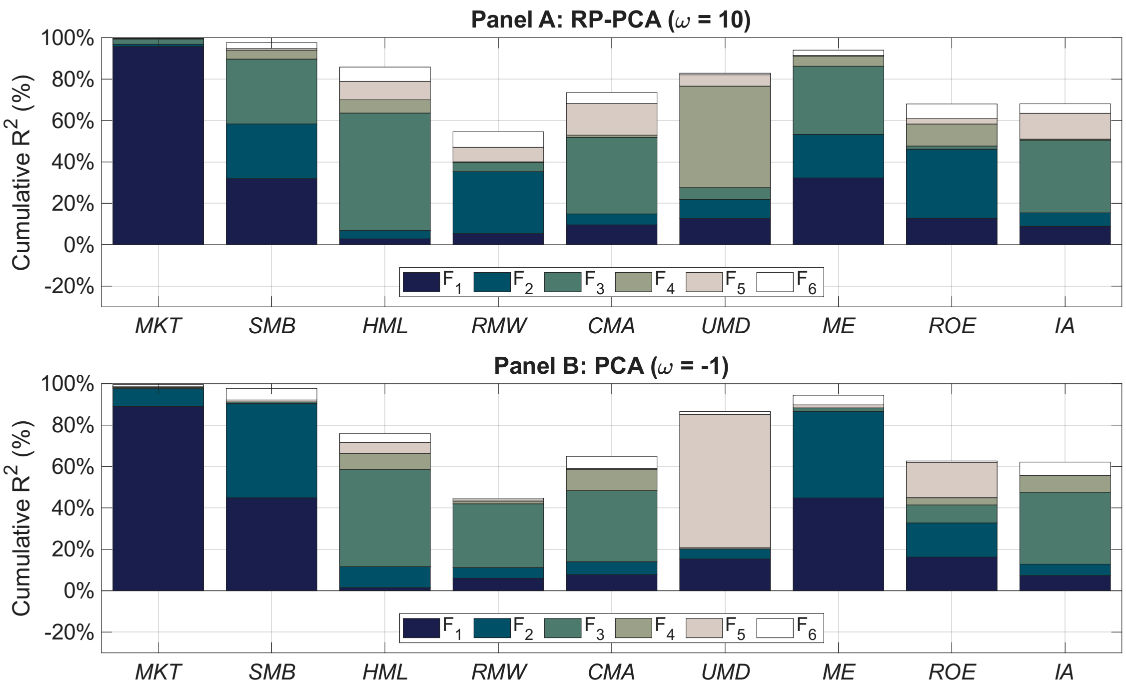

Figure 2. Explained Variation in Common Factors by Latent Factors. The figure shows the R^2 values obtained from regressing the excess returns of common factors on the six latent factors extracted from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b). The results in Panel A (Panel B) correspond to the latent factor estimation with the RP-PCA penalty parameter $\omega = 10$ ($\omega = -1$). To produce the results in each panel, we run six regressions for each common factor. The regressions for a given common factor sequentially add one of the latent factors.

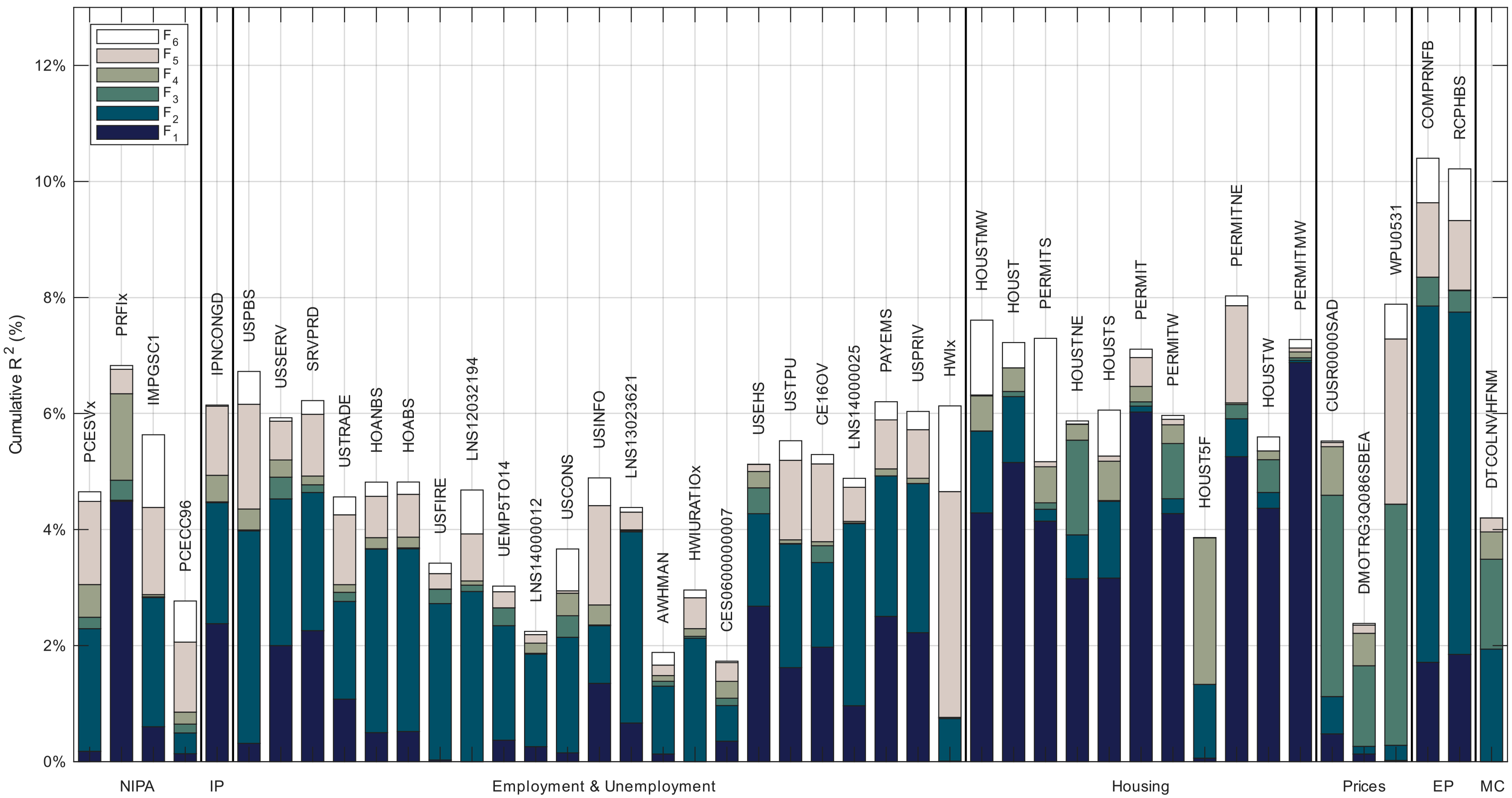

Figure 3. Explained Variation in Macroeconomic Variables by Latent Factors. The figure shows the R^2 values obtained from regressing the macroeconomic factors on the six latent factors extracted from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the RP-PCA penalty parameter $\omega = 10$. To produce the results, we run six regressions for each macroeconomic variable. The regressions for a given variable sequentially add one of the latent factors. The macroeconomic variable TNWMVBSNNCBx from the non-household balance sheets category has an R^2 value of 28.85% and is omitted from the plot for readability.

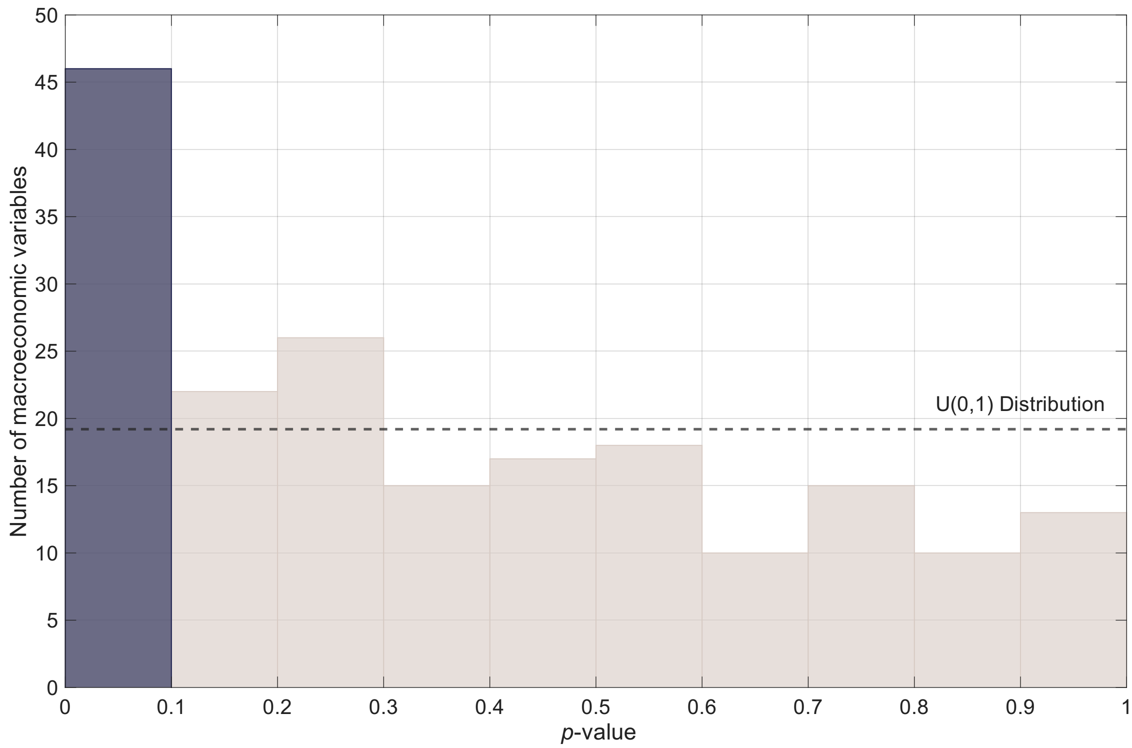

Figure 4. Histogram of p-values for Macroeconomic Risk Premium Estimates. The figure shows a histogram of asymptotic p-values across the full set of 192 macroeconomic variables from two-sided tests of the null hypothesis that each macroeconomic factor has a zero risk premium. Risk premia are estimated using the augmented three-pass approach of Giglio and Xiu (2021). The latent factors are estimated from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the number of latent factors $K = 6$ and the RP-PCA penalty parameter $\omega = 10$.

Internet Appendix
(Not for Publication)

"On the Macroeconomic Foundations of the Anomaly Zoo"

A Data Description

In this section, we provide additional details on our data sources.

A.1 Test Assets

Our empirical tests on latent factor extraction and risk premium estimation are based on a broad panel of excess returns for 865 equity style portfolios. We obtain portfolio return data from two sources: Kenneth French's data library and the Open Source Asset Pricing (OSAP) database compiled by Andrew Chen and Tom Zimmermann. We summarize these data in Table IA.I. The test assets include 12 sets of portfolios that collectively constitute the 315 portfolios taken from Kenneth French's data library and the 110 sets of anomaly quintile portfolios from OSAP.

Our empirical tests on asset pricing anomalies use returns for long and short tercile portfolios from the Global Factor Data website maintained by Theis Jensen, Bryan Kelly, and Lasse Pedersen. In Table IA.II, we list the 149 sets of anomaly portfolios that have complete data coverage over our sample period. The panels of the table are grouped by anomaly variable category. For each set of portfolios, the table reports the anomaly name, a reference to the original study documenting the anomaly, and a brief description of the sorting variable.

A.2 Macroeconomic Factors

In Table IA.III, we report the 192 candidate macroeconomic factors from the FRED-QD database. We exclude factors from FRED-QD that are classified as financial factors and factors that lack data coverage over our full sample period. The panels of the table are grouped by macroeconomic variable category. For each variable, the table reports the series name, a brief description, the units of measurement, and a transformation code indicating the method for creating a stationary time series.

B Additional Results

In this section, we present and discuss supplementary empirical results and robustness tests.

B.1 RP-PCA Penalty Parameter

In Section 4.1, we describe our choices for the number of latent factors (K) and the penalty parameter (ω) used in the RP-PCA estimation to recover the factor space. Our base case ultimately uses $K = 6$ and $\omega = 10$. The discussion in the text focuses primarily on the statistical and economic criteria used to inform the choice of K. In Table IA.IV, we summarize the performance of RP-PCA models with $K = 6$ and various values for ω based on (i) the maximum Sharpe ratio of the implied tangency portfolio, (ii) the average ratio of idiosyncratic variance to total variance, (iii) the root-mean-square pricing error from the time-series regressions, (iv) the cross-sectional R^2, and (v) the average absolute pricing error from the cross-sectional regression. The estimation is based on a cross section of 865 equity style portfolios. We consider results for $\omega \in \{-1, 0, 5, 10, 20, 30, 40, 50\}$. Standard PCA estimation corresponds to $\omega = -1$.

Standard PCA focuses on explaining time-series variation in test asset returns, whereas RP-PCA with $\omega > -1$ searches for factors that capture both time-series variation in returns and cross-sectional differences in average returns. We thus expect, for a given choice of K, idiosyncratic variance to be smallest under PCA estimation. Table IA.IV confirms this result. For RP-PCA estimation, increasing ω places more weight on explaining the cross section of average returns, so there is an expected trade-off: higher ω leads to a higher R^2 and lower average absolute pricing error in the cross-sectional regression, but at the cost of higher idiosyncratic risk in the time-series regressions. The results in Table IA.IV show that $\omega = 10$ offers a reasonable balance of these effects. Most of the incremental gains from estimation with large positive ω values in the maximum Sharpe ratio, cross-sectional R^2, and cross-sectional pricing errors relative to PCA are reached at $\omega = 10$. The pattern in average idiosyncratic variance across ω values follows the expected pattern, but the differences are modest. Our base case of $\omega = 10$ also leads to smaller absolute time-series regression intercepts relative to RP-PCA estimation with even higher ω.

B.2 Spanning Regressions for PCA Factors

In Table III, we report results from spanning regressions of the six RP-PCA factors on traditional asset pricing factors. Table IA.V presents analogous results for the six PCA factors.

B.3 Macroeconomic Factor Risk Premia

In Table IV, we report estimates of the risk premia for macroeconomic factors using the augmented three-pass estimation approach of Giglio and Xiu (2021). The table covers the 46 macroeconomic factors (of the 192 total candidate factors) with statistically significant risk premia at the 10% level. In Table IA.VI, we present results for the remaining 146 macroeconomic factors.

For the results in Tables IV and IA.VI, the first pass of the estimation relies on RP-PCA to recover the latent factor space. In Table IA.VII, we summarize the results for risk premia estimation based on Giglio and Xiu's (2021) three-pass approach with standard PCA estimation in the first pass. The table focuses on macroeconomic factors with statistically significant risk premia at the 10% level.

B.4 Comparison of Risk Premium Estimation Methods

In Table IA.VIII, we provide a summary comparison of the risk premium estimation results from the augmented three-pass approach of Giglio and Xiu (2021) with those from the standard two-pass approach. Following Giglio and Xiu (2021), we consider, for each macroeconomic factor, a version of the two-pass procedure that controls for the market factor (*MKT*) and one that controls for the three Fama-French factors (*MKT*, *SMB*, and *HML*). In Panel A, the test assets for the two-pass procedure are the same 865 characteristic-sorted equity portfolios used in the base case three-pass estimation in the paper. In Panel B, the test assets are a smaller cross section of 30 portfolios from Liu and Zhang (2008) that includes 10 value-weighted decile portfolios formed from univariate sorts on each of size, book-to-market equity, and momentum.[12]

Across the 192 macroeconomic factors, Table IA.VIII shows the number of factors that are statistically significant at the 10% level under the augmented three-pass specification and the various two-pass specifications. The table also reports, for each two-pass specification, the median ratio of the absolute

[12]The decile portfolio returns are from Kenneth French's data library.

risk premium estimate from the two-pass approach to the absolute risk premium estimate from the augmented three-pass approach. In the two-pass estimation, we restrict the intercept in the second-pass regression to be zero (consistent with the three-pass estimation) and assess statistical significance using Shanken (1992) standard errors. Each panel provides a further breakdown of the results by macroeconomic variable category.

There are three key takeaways from the results in Table IA.VIII. First, both the number of significant macroeconomic variables and the magnitudes of the risk premium estimates are inflated under the two-pass procedure. Whereas the three-pass method identifies 46 significant macroeconomic factors, the two-pass method yields between 107 and 167. Across all 192 candidate factors, the median inflation in the risk price coefficient under the two-pass procedure relative to the three-pass procedure is between 4.9 and 23.1 times. These findings are primarily attributable to measurement error in the macroeconomic factors. In particular, the low R^2s in the projections of the macroeconomic factors onto the latent factor space (e.g., Table IV and Figure 3) suggest that most factors contain considerable noise unrelated to asset returns. This measurement error in the factors impacts the two-pass estimation approach by deflating the time-series loadings in the first-pass regressions and inflating the risk prices in the second pass.

Second, there is clear evidence of omitted variable bias in the two-pass estimation results. For a given set of test assets, the number of significant macroeconomic factors varies materially using different sets of control factors. In unreported results, we also find that there are extreme differences in the point estimates of the risk prices for many factors under alternative specifications of the control factors.

Third, the number of statistically significant macroeconomic factors and the magnitudes of the estimated risk prices are generally higher using the 30 Liu and Zhang (2008) test assets (Panel B) rather than the broader cross section of 865 test assets (Panel A). This pattern echoes the findings of Lewellen, Nagel, and Shanken (2010), who show that two-pass specifications based on small cross sections with a low-dimensional factor structure often yield misleading empirical support for a given model.

In sum, a comparison of the three-pass and two-pass results confirms that the two-pass procedure suffers from measurement error and omitted variable biases and that the impact of these biases is severe in our application measuring risk premia for macroeconomic factors. The two-pass specifications popular in prior work also tend to be sensitive to the choice of test assets. Our three-pass risk premium estimation tests summarized in Table IV overcome these limitations and offer a comprehensive and reliable characterization of macroeconomic risk premia in the cross section of stock returns.

B.5 Summary Statistics for Anomaly Portfolios

In Table V, we report average returns and CAPM regression results for the 104 long-short anomaly portfolios (of the 149 total candidate anomaly portfolios) with statistically significant CAPM alphas at the 5% level. For completeness, we present the results for the remaining 45 anomaly portfolios in Table IA.IX.

B.6 Robustness Tests

Our main conclusions on the pervasiveness of risk premia associated with macroeconomic factors (Table IV) and the ability of macroeconomic mimicking portfolios to resolve a wide range of asset pricing anomalies (Table VI) are potentially sensitive to the empirical implementation of the latent factor estimation procedure. The most critical design choices include the RP-PCA penalty parameter, the number of latent factors, and the composition of the panel of equity portfolios used for estimation. Although we have established that our baseline choices are guided by several statistical and economic criteria, we evaluate the robustness of our findings to alternative specifications.

We present the robustness results in Table IA.X. In Panel A, we provide the results from our base case design. We consider the impact of modifying the RP-PCA penalty parameter, the number of latent RP-PCA factors, and the test assets in Panels B, C, and D, respectively. For each specification, we show the number of the 192 candidate macroeconomic factors with statistically significant risk premia in the augmented Giglio and Xiu (2021) procedure and summary results on the performance of the macroeconomic mimicking portfolios (corresponding to the factors with statistically significant risk premia) in resolving the 104 CAPM anomalies. The latter asset pricing tests focus on the number of significant anomalies and the average CAPM alpha reduction. For each measure, we report the best performance across the two-factor models and identify the best performing model.

The results in Panel B suggest that our conclusions regarding the number of significantly priced macroeconomic factors are robust to the choice of the RP-PCA penalty parameter. Across the specifications summarized in the table, the number of significant factors ranges from 38 (for $\omega = 40$ and $\omega = 50$) to 50 (for $\omega = 5$). All specifications produce a total number of significant factors close to our base case total of 46. Based on the performance of the two-factor models in resolving CAPM anomalies, the results are quite similar for any choice of $\omega \geq 5$. These specifications produce comparable results according to the number of significant anomalies, the average CAPM alpha reduction, and the identities of the best performing models. Two-factor model performance deteriorates, however, when the latent factors are extracted via PCA (i.e., the $\omega = -1$ case). This finding reinforces the importance of incorporating Lettau and Pelger's (2020a,b) RP-PCA approach in the first pass of the estimation to identify latent factors that capture both time-series variation in returns and cross-sectional patterns in average returns.

In Panel C, we summarize the sensitivity of the results to the number of latent RP-PCA factors. We present results for $3 \leq K \leq 6$ (covering the range of values suggested by the statistical diagnostics summarized in Table I) and for $K \in \{7, 13\}$ (corresponding to the lowest and highest values considered by Giglio and Xiu (2021)). The number of macroeconomic variables with significant risk premia varies somewhat with K, but there is no clear monotonic relation. All specifications with intermediate values of K that are close to our base case (i.e., for $4 \leq K \leq 7$) produce similar results based on best two-factor model performance in explaining CAPM anomalies. The best two-factor model performance is diminished at extreme values of K (i.e., for $K = 3$ and $K = 13$), but the best two-factor models continue to explain anomaly returns at levels comparable with the leading multifactor benchmarks with characteristics-based factors.

Finally, we show in Panel D how the results change if we use either the 315 Kenneth French portfolios or the 550 OSAP portfolios for latent factor extraction rather than the combined set of 865 portfolios as in our baseline analysis. There are 48 macroeconomic factors with significant risk premia based on the Kenneth French portfolios alone versus 21 based on the OSAP portfolios alone. The performance of the macroeconomic two-factor models under either alternative specification is similar to that of the base case.

Table IA.I: Test Assets for Estimation of Macroeconomic Risk Premia

The table lists the 315 value-weighted equity portfolios from Kenneth French's data library and 550 value-weighted anomaly portfolios from the OSAP anomaly database used in the augmented Giglio and Xiu (2021) procedure. We construct a quarterly excess return series for each portfolio covering the period from 1970:Q1 to 2024:Q4.

Description	Source	Number
Portfolios formed on size and book-to-market	Kenneth French's data library	25
Portfolios formed on size and operating profitability	Kenneth French's data library	25
Portfolios formed on size and investment	Kenneth French's data library	25
Portfolios formed on size and momentum	Kenneth French's data library	25
Portfolios formed on size and short-term reversal	Kenneth French's data library	25
Portfolios formed on size and long-term reversal	Kenneth French's data library	25
Portfolios formed on size and accruals	Kenneth French's data library	25
Portfolios formed on size and beta	Kenneth French's data library	25
Portfolios formed on size and net share issues	Kenneth French's data library	35
Portfolios formed on size and variance	Kenneth French's data library	25
Portfolios formed on size and residual variance	Kenneth French's data library	25
Industry portfolios	Kenneth French's data library	30
Quintile portfolios formed on 110 anomaly variables	OSAP anomaly database	550

Table IA.II: Test Assets from the Global Factor Data Website

The table lists the 149 long-short anomaly portfolios from the Global Factor Data website used in our empirical analysis. The data are described in Jensen, Kelly, and Pedersen (2023). The panels of the table are grouped by anomaly variable category. We construct a quarterly excess return series for each portfolio covering the period from 1970:Q1 to 2024:Q4.

ID	Name	Original study	Description
		Panel A: Momentum	
1	prc_highprc_252d	George and Hwang (2004)	Current price to high price over last year
2	resff3_12_1	Blitz, Huij, and Martens (2011)	Residual momentum $t-12$ to $t-1$
3	resff3_6_1	Blitz, Huij, and Martens (2011)	Residual momentum $t-6$ to $t-1$
4	ret_12_1	Jegadeesh and Titman (1993)	Price momentum $t-12$ to $t-1$
5	ret_3_1	Jegadeesh and Titman (1993)	Price momentum $t-3$ to $t-1$
6	ret_6_1	Jegadeesh and Titman (1993)	Price momentum $t-6$ to $t-1$
7	ret_9_1	Jegadeesh and Titman (1993)	Price momentum $t-9$ to $t-1$
8	seas_1_1na	Heston and Sadka (2008)	Year 1-lagged return, nonannual
		Panel B: Value	
9	at_me	Fama and French (1992)	Assets-to-market
10	be_me	Rosenberg, Reid, and Lanstein (1985)	Book-to-market equity
11	bev_mev	Penman, Richardson, and Tuna (2007)	Book-to-market enterprise value
12	chcsho_12m	Pontiff and Woodgate (2008)	Net stock issues
13	debt_me	Bhandari (1988)	Debt-to-market
14	div12m_me	Litzenberger and Ramaswamy (1979)	Dividend yield
15	ebitda_mev	Loughran and Wellman (2011)	EBITDA-to-market enterprise value
16	eq_dur	Dechow, Sloan, and Soliman (2004)	Equity duration
17	eqnpo_12m	Daniel and Titman (2006)	Equity net payout
18	fcf_me	Lakonishok, Schleifer, and Vishny (1994)	Free cash flow-to-price
19	ival_me	Frankel and Lee (1998)	Intrinsic value-to-market
20	ni_me	Basu (1983)	Earnings-to-price
21	ocf_me	Desai, Rajgopal, and Venkatachalam (2004)	Operating cash flow-to-market
22	sale_me	Barbee Jr., Mukherji, and Raines (1996)	Sales-to-market
		Panel C: Investment	
23	aliq_at	Ortiz-Molina and Phillips (2014)	Liquidity of book assets
24	at_gr1	Cooper, Gulen, and Schill (2008)	Asset growth

(Continued on next page)

Table IA.II (Continued)

ID	Name	Original study	Description
		Panel C: Investment (Continued)	
25	be_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in common equity
26	capex_abn	Titman, Wei, and Xie (2004)	Abnormal corporate investment
27	capx_gr1	Xie (2001)	CAPEX growth (1 year)
28	capx_gr2	Anderson and Garcia-Feijoo (2006)	CAPEX growth (2 years)
29	capx_gr3	Anderson and Garcia-Feijoo (2006)	CAPEX growth (3 years)
30	coa_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in current operating assets
31	col_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in current operating liabilities
32	cowc_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in current operating working capital
33	debt_gr3	Lyandres, Sun, and Zhang (2008)	Growth in book debt (3 years)
34	emp_gr1	Belo, Lin, and Bazdresch (2014)	Hiring rate
35	fnl_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in financial liabilities
36	inv_gr1	Belo and Lin (2012)	Inventory growth
37	inv_gr1a	Thomas and Zhang (2002)	Inventory change
38	lnoa_gr1a	Fairfield, Whisenant, and Yohn (2003)	Change in long-term net operating assets
39	mispricing_mgmt	Stambaugh and Yuan (2017)	Mispricing factor: Management
40	ncoa_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in noncurrent operating assets
41	ncol_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in noncurrent operating liabilities
42	nfna_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in net financial assets
43	ni_ar1	Francis, LaFond, Olsson, and Schipper (2004)	Earnings persistence
44	nncoa_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in net noncurrent operating assets
45	noa_at	Hirshleifer, Hou, Teoh, and Zhang (2004)	Net operating assets
46	noa_gr1a	Hirshleifer, Hou, Teoh, and Zhang (2004)	Change in net operating assets
47	oaccruals_at	Sloan (1996)	Operating accruals
48	oaccruals_ni	Hafzalla, Lundholm, and Van Winkle (2011)	Percent operating accruals
49	ppeinv_gr1a	Lyandres, Sun, and Zhang (2008)	Change in PPE and inventory
50	ret_60_12	De Bondt and Thaler (1985)	Long-term reversal
51	sale_gr1	Lakonishok, Shleifer, and Vishny (1994)	Sales growth (1 year)
52	sale_gr3	Lakonishok, Shleifer, and Vishny (1994)	Sales growth (3 years)
53	saleq_gr1		Sales growth (1 quarter)
54	seas_16_20na	Heston and Sadka (2008)	Years 16–20 lagged returns, nonannual
55	seas_2_5na	Heston and Sadka (2008)	Years 2–5 lagged returns, nonannual
56	taccruals_at	Richardson, Sloan, Soliman, and Tuna (2005)	Total accruals
57	taccruals_ni	Hafzalla, Lundholm, and Van Winkle (2011)	Percent total accruals

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Table IA.II (Continued)

ID	Name	Original study	Description
		Panel D: Profitability	
58	at_turnover	Haugen and Baker (1996)	Capital turnover
59	cop_at		Cash-based operating profits-to-book assets
60	cop_atl1	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)	Cash-based operating profits-to-lagged book assets
61	dgp_dsale	Abarbanell and Bushee (1998)	Change gross margin minus change sales
62	dolvol_var_126d	Chordia, Subrahmanyam, and Anshuman (2001)	Coefficient of variation for dollar trading volume
63	dsale_dinv	Abarbanell and Bushee (1998)	Change sales minus change inventory
64	dsale_drec	Abarbanell and Bushee (1998)	Change sales minus change receivables
65	dsale_dsga	Abarbanell and Bushee (1998)	Change sales minus change SG&A
66	ebit_bev	Soliman (2008)	Return on net operating assets
67	ebit_sale	Soliman (2008)	Profit margin
68	f_score	Piotroski (2000)	Pitroski F-score
69	gp_at	Novy-Marx (2013)	Gross profits-to-assets
70	gp_atl1		Gross profits-to-lagged assets
71	mispricing_perf	Stambaugh and Yuan (2017)	Mispricing factor: Performance
72	ni_be	Haugen and Baker (1996)	Return on equity
73	ni_inc8q	Barth, Elliott, and Finn (1999)	Number of consecutive quarters with earnings increases
74	niq_at	Balakrishnan, Bartov, and Faurel (2010)	Quarterly return on assets
75	niq_at_chg1		Change in quarterly return on assets
76	niq_be	Hou, Xue, and Zhang (2015)	Quarterly return on equity
77	niq_be_chg1		Change in quarterly return on equity
78	niq_su	Foster, Olsen, and Shevlin (1984)	Standardized earnings surprise
79	o_score	Dichev (1998)	Ohlson O-score
80	ocf_at	Bouchaud, Krueger, Landier, and Thesmar (2019)	Operating cash flow-to-assets
81	ocf_at_chg1	Bouchaud, Krueger, Landier, and Thesmar (2019)	Change in operating cash flow to assets
82	op_at		Operating profits-to-book assets
83	op_atl1	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)	Operating profits-to-lagged book assets
84	ope_be	Fama and French (2015)	Operating profits-to-book equity
85	ope_bel1		Operating profits-to-lagged book equity
86	opex_at	Novy-Marx (2011)	Operating leverage
87	qmj	Asness, Frazzini, and Pedersen (2019)	Quality minus Junk: Composite
88	qmj_growth	Asness, Frazzini, and Pedersen (2019)	Quality minus Junk: Growth
89	qmj_prof	Asness, Frazzini, and Pedersen (2019)	Quality minus Junk: Profitability
90	qmj_safety	Asness, Frazzini, and Pedersen (2019)	Quality minus Junk: Safety

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Table IA.II (Continued)

ID	Name	Original study	Description
		Panel D: Profitability (Continued)	
91	ret_12_7	Novy-Marx (2012)	Price momentum $t-12$ to $t-7$
92	sale_bev	Soliman (2008)	Asset turnover
93	sale_emp_gr1	Abarbanell and Bushee (1998)	Labor force efficiency
94	saleq_su	Jegadeesh and Livnat (2006)	Standardized revenue surprise
95	seas_1_1an	Heston and Sadka (2008)	Year 1-lagged return, annual
96	tax_gr1a	Thomas and Zhang (2011)	Tax expense surprise
97	turnover_var_126d	Chordia, Subrahmanyam, and Anshuman (2001)	Coefficient of variation for share turnover
		Panel E: Intangibles	
98	age	Jiang, Lee, and Zhang (2005)	Firm age
99	aliq_mat	Ortiz-Molina and Phillips (2014)	Liquidity of market assets
100	at_be	Fama and French (1992)	Book leverage
101	bidaskhl_21d	Corwin and Schultz (2012)	High-low bid-ask spread
102	cash_at	Palazzo (2012)	Cash-to-assets
103	corr_1260d	Asness, Frazzini, Gormsen, and Pedersen (2020)	Market correlation
104	coskew_21d	Harvey and Siddique (2000)	Coskewness
105	dbnetis_at	Bradshaw, Richardson, and Sloan (2006)	Net debt issuance
106	kz_index	Lamont, Polk, and Saaá-Requejo (2001)	Kaplan-Zingales index
107	lti_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in long-term investments
108	netdebt_me	Penman, Richardson, and Tuna (2007)	Net debt-to-price
109	ni_ivol	Francis, LaFond, Olsson, and Schipper (2004)	Earnings volatility
110	pi_nix	Lev and Nissim (2004)	Taxable income-to-book income
111	rd5_at	Li (2011)	R&D capital-to-book assets
112	rd_sale	Chan, Lakonishok, and Sougiannis (2001)	R&D-to-sales
113	seas_11_15an	Heston and Sadka (2008)	Years 11–15 lagged returns, annual
114	seas_11_15na	Heston and Sadka (2008)	Years 11–15 lagged returns, nonannual
115	seas_16_20an	Heston and Sadka (2008)	Years 16–20 lagged returns, annual
116	seas_2_5an	Heston and Sadka (2008)	Years 2–5 lagged returns, annual
117	seas_6_10an	Heston and Sadka (2008)	Years 6–10 lagged returns, annual
118	sti_gr1a	Richardson, Sloan, Soliman, and Tuna (2005)	Change in short-term investments
119	tangibility	Hahn and Lee (2009)	Asset tangibility
120	z_score	Dichev (1998) Altman	Z-score

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Table IA.II (Continued)

ID	Name	Original study	Description
		Panel F: Trading Frictions	
121	ami_126d	Amihud (2002)	Amihud measure
122	beta_60m	Fama and MacBeth (1973)	Market beta
123	beta_dimson_21d	Dimson (1979)	Dimson beta
124	betabab_1260d	Frazzini and Pedersen (2014)	Frazzini-Pedersen market beta
125	betadown_252d	Ang, Chen, and Xing (2006)	Downside beta
126	dolvol_126d	Brennan, Chordia, and Subrahmanyam (1998)	Dollar trading volume
127	earnings_variability	Francis, LaFond, Olsson, and Schipper (2004)	Earnings variability
128	iskew_capm_21d		Idiosyncratic skewness from the CAPM
129	iskew_ff3_21d	Bali, Engle, and Murray (2016)	Idiosyncratic skewness from the Fama-French 3-factor model
130	iskew_hxz4_21d		Idiosyncratic skewness from the q-factor model
131	ivol_capm_21d		Idiosyncratic volatility from the CAPM (21 days)
132	ivol_capm_252d	Ali, Hwang, and Trombley (2003)	Idiosyncratic volatility from the CAPM (252 days)
133	ivol_ff3_21d	Ang, Hodrick, Xing, and Zhang (2006)	Idiosyncratic volatility from the Fama-French 3-factor model
134	ivol_hxz4_21d		Idiosyncratic volatility from the q-factor model
135	market_equity	Banz (1981)	Market equity
136	ocfq_saleq_std	Huang (2009)	Cash flow volatility
137	prc	Miller and Scholes (1982)	Price per share
138	rd_me	Chan, Lakonishok, and Sougiannis (2001)	R&D-to-market
139	ret_1_0	Jegadeesh (1990)	Short-term reversal
140	rmax1_21d	Bali, Cakici, and Whitelaw (2011)	Maximum daily return
141	rmax5_21d	Bali, Brown, and Tang (2017)	Highest 5 days of return
142	rmax5_rvol_21d	Asness, Frazzini, Gormsen, and Pedersen (2020)	Highest 5 days of return scaled by volatility
143	rskew_21d	Bali, Engle, and Murray (2016)	Total skewness
144	rvol_21d	Ang, Hodrick, Xing, and Zhang (2006)	Return volatility
145	seas_6_10na	Heston and Sadka (2008)	Years 6–10 lagged returns, nonannual
146	turnover_126d	Datar, Naik, and Radcliffe (1998)	Share turnover
147	zero_trades_126d	Liu (2006)	Number of zero trades with turnover as tiebreaker (6 months)
148	zero_trades_21d	Liu (2006)	Number of zero trades with turnover as tiebreaker (1 month)
149	zero_trades_252d	Liu (2006)	Number of zero trades with turnover as tiebreaker (12 months)

Table IA.III: Macroeconomic Variables

The table summarizes the macroeconomic time series considered in the paper. All variables are from the current version of the FRED-QD database described in McCracken and Ng (2021). For each variable, the table reports the variable's name, description, units of measurement, and transformation code. For a given series $\{z_t\}_{t=-1}^{T}$, the transformation codes take the following forms: (1) no transformation, (2) Δz_t, (3) $\Delta^2 z_t$, (4) $\log(z_t)$, (5) $\Delta\log(z_t)$, (6) $\Delta^2\log(z_t)$, and (7) $z_t/z_{t-1}-1$. The panels of the table are grouped by variable category. Each variable is available at the quarterly frequency over the period from 1970:Q1 to 2024:Q4.

ID	Name	Description	Units	tcode
		Panel A: NIPA		
1	GDPC1	Real gross domestic product	Billions of chained 2017 USD	5
2	PCECC96	Real personal consumption expenditures	Billions of chained 2017 USD	5
3	PCDGx	Real personal consumption expenditures: Durable goods	Billions of chained 2017 USD	5
4	PCESVx	Real personal consumption expenditures: Services	Billions of chained 2017 USD	5
5	PCNDx	Real personal consumption expenditures: Nondurable goods	Billions of chained 2017 USD	5
6	GPDIC1	Real gross private domestic investment	Billions of chained 2017 USD	5
7	FPIx	Real private fixed investment	Billions of chained 2017 USD	5
8	Y033RC1Q027SBEAx	Real gross private domestic investment: Fixed investment: Nonresidential: Equipment	Billions of chained 2017 USD	5
9	PNFIx	Real private fixed investment: Nonresidential	Billions of chained 2017 USD	5
10	PRFIx	Real private fixed investment: Residential	Billions of chained 2017 USD	5
11	A014RE1Q156NBEA	Shares of gross domestic product: Gross private domestic investment: Change in private inventories	Percent	1
12	GCEC1	Real government consumption expenditures and gross investment	Billions of chained 2017 USD	5
13	A823RL1Q225SBEA	Real government consumption expenditures and gross investment: Federal	Percent change	1
14	FGRECPTx	Real federal government current receipts	Billions of chained 2017 USD	5
15	SLCEx	Real government state and local consumption expenditures	Billions of chained 2017 USD	5
16	EXPGSC1	Real exports of goods and services	Billions of chained 2017 USD	5
17	IMPGSC1	Real imports of goods and services	Billions of chained 2017 USD	5
18	DPIC96	Real disposable personal income	Billions of chained 2017 USD	5
19	OUTNFB	Nonfarm business sector: Real output	Index 2017=100	5
20	OUTBS	Business sector: Real output	Index 2017=100	5
21	B020RE1Q156NBEA	Shares of gross domestic product: Exports of goods and services	Percent	2
22	B021RE1Q156NBEA	Shares of gross domestic product: Imports of goods and services	Percent	2

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel B: Industrial Production		
23	INDPRO	Industrial Production Index	Index 2017=100	5
24	IPFINAL	Industrial production: Final products (Market group)	Index 2017=100	5
25	IPCONGD	Industrial production: Consumer goods	Index 2017=100	5
26	IPMAT	Industrial production: Materials	Index 2017=100	5
27	IPDMAT	Industrial production: Durable materials	Index 2017=100	5
28	IPNMAT	Industrial production: Nondurable materials	Index 2017=100	5
29	IPDCONGD	Industrial production: Durable consumer goods	Index 2017=100	5
30	IPB51110SQ	Industrial production: Durable goods: Automotive products	Index 2017=100	5
31	IPNCONGD	Industrial production: Nondurable consumer goods	Index 2017=100	5
32	IPBUSEQ	Industrial production: Business equipment	Index 2017=100	5
33	IPB51220SQ	Industrial production: Consumer energy products	Index 2017=100	5
34	TCU	Capacity utilization: Total industry	Percent of capacity	1
35	CUMFNS	Capacity utilization: Manufacturing (SIC)	Percent of capacity	1
36	IPMANSICS	Industrial production: Manufacturing (SIC)	Index 2017=100	5
37	IPB51222S	Industrial production: Residential utilities	Index 2017=100	5
38	IPFUELS	Industrial production: Fuels	Index 2017=100	5
		Panel C: Employment and Unemployment		
39	PAYEMS	All employees: Total nonfarm	Thousands of persons	5
40	USPRIV	All employees: Total private industries	Thousands of persons	5
41	MANEMP	All employees: Manufacturing	Thousands of persons	5
42	SRVPRD	All employees: Service-providing industries	Thousands of persons	5
43	USGOOD	All employees: Goods-producing industries	Thousands of persons	5
44	DMANEMP	All employees: Durable goods	Thousands of persons	5
45	NDMANEMP	All employees: Nondurable goods	Thousands of persons	5
46	USCONS	All employees: Construction	Thousands of persons	5
47	USEHS	All employees: Education and health services	Thousands of persons	5
48	USFIRE	All employees: Financial activities	Thousands of persons	5
49	USINFO	All employees: Information services	Thousands of persons	5
50	USPBS	All employees: Professional and business services	Thousands of persons	5
51	USLAH	All employees: Leisure and hospitality	Thousands of persons	5
52	USSERV	All employees: Other services	Thousands of persons	5
53	USMINE	All employees: Mining and logging	Thousands of persons	5

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel C: Employment and Unemployment (Continued)		
54	USTPU	All employees: Trade, transportation and utilities	Thousands of persons	5
55	USGOVT	All employees: Government	Thousands of persons	5
56	USTRADE	All employees: Retail trade	Thousands of persons	5
57	USWTRADE	All employees: Wholesale trade	Thousands of persons	5
58	CES9091000001	All employees: Government: Federal	Thousands of persons	5
59	CES9092000001	All employees: Government: State government	Thousands of persons	5
60	CES9093000001	All employees: Government: Local government	Thousands of persons	5
61	CE16OV	Civilian employment	Thousands of persons	5
62	CIVPART	Civilian labor force participation rate	Percent	2
63	UNRATE	Civilian unemployment rate	Percent	2
64	UNRATESTx	Unemployment rate less than 27 weeks	Percent	2
65	UNRATELTx	Unemployment rate for more than 27 weeks	Percent	2
66	LNS14000012	Unemployment rate - 16 to 19 years	Percent	2
67	LNS14000025	Unemployment rate - 20 years and over, men	Percent	2
68	LNS14000026	Unemployment rate - 20 years and over, women	Percent	2
69	UEMPLT5	Number of civilians unemployed less than 5 weeks	Thousands of persons	5
70	UEMP5TO14	Number of civilians unemployed for 5 to 14 weeks	Thousands of persons	5
71	UEMP15T26	Number of civilians unemployed for 15 to 26 weeks	Thousands of persons	5
72	UEMP27OV	Number of civilians unemployed for 27 weeks and over	Thousands of persons	5
73	LNS13023621	Unemployment level - Job losers	Thousands of persons	5
74	LNS13023557	Unemployment level - Reentrants to labor force	Thousands of persons	5
75	LNS13023705	Unemployment level - Job leavers	Thousands of persons	5
76	LNS13023569	Unemployment level - New entrants	Thousands of persons	5
77	LNS12032194	Employment level - Part-time for economic reasons, all industries	Thousands of persons	5
78	HOABS	Business sector: Hours of all persons	Index 2017=100	5
79	HOANBS	Nonfarm business sector: Hours of all persons	Index 2017=100	5
80	AWHMAN	Average weekly hours of production and nonsupervisory employees: Manufacturing	Hours	1
81	AWHNONAG	Average weekly hours of production and nonsupervisory employees: Total private	Hours	2
82	AWOTMAN	Average weekly overtime hours of production and nonsupervisory employees: Manufacturing	Hours	2
83	HWIx	Help-Wanted Index		1
84	UEMPMEAN	Average (mean) duration of unemployment	Weeks	2

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel C: Employment and Unemployment (Continued)		
85	CES0600000007	Average weekly hours of production and nonsupervisory employees: Goods-producing		2
86	HWIURATIOx	Ratio of help wanted to number of unemployed		2
87	CLAIMSx	Initial claims		5
		Panel D: Housing		
88	HOUST	Housing starts: Total: New privately owned housing units started	Thousands of units	5
89	HOUST5F	Privately owned housing starts: 5-unit structures or more	Thousands of units	5
90	PERMIT	New private housing units authorized by building permits	Thousands of units	5
91	HOUSTMW	Housing starts in Midwest census region	Thousands of units	5
92	HOUSTNE	Housing starts in Northeast census region	Thousands of units	5
93	HOUSTS	Housing starts in South census region	Thousands of units	5
94	HOUSTW	Housing starts in West census region	Thousands of units	5
95	PERMITNE	New private housing units authorized by building permits in the Northeast census region	Thousands, SAAR	5
96	PERMITMW	New private housing units authorized by building permits in the Midwest census region	Thousands, SAAR	5
97	PERMITS	New private housing units authorized by building permits in the South census region	Thousands, SAAR	5
98	PERMITW	New private housing units authorized by building permits in the West census region	Thousands, SAAR	5
		Panel E: Inventories, Orders, and Sales		
99	CMRMTSPLx	Real manufacturing and trade industries sales	Millions of chained 2017 USD	5
100	RSAFSx	Real retail and food services sales	Millions of chained 2017 USD	5
101	AMDMNOx	Real manufacturers' new orders: Durable goods	Millions of 2017 USD	5
102	AMDMUOx	Real value of manufacturers' unfilled orders for durable goods industries	Millions of 2017 USD	5
103	ANDENOx	Real value of manufacturers' new orders for capital goods: Nondefense capital goods industries	Millions of 2017 USD	5
104	INVCQRMTSPL	Real manufacturing and trade inventories	Millions of 2017 USD	5
105	BUSINVx	Total business inventories	Millions of USD	5
106	ISRATIOx	Total business: Inventories to sales ratio		2

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel F: Prices		
107	PCECTPI	Personal consumption expenditures: Chain-type price index	Index 2017=100	6
108	PCEPILFE	Personal consumption expenditures excluding food and energy: Chain-type price index	Index 2017=100	6
109	GDPCTPI	Gross domestic product: Chain-type price index	Index 2017=100	6
110	GPDICTPI	Gross private domestic investment: Chain-type price index	Index 2017=100	6
111	IPDBS	Business sector: Implicit price deflator	Index 2017=100	6
112	DGDSRG3Q086SBEA	Personal consumption expenditures: Goods (chain-type price index)		6
113	DDURRG3Q086SBEA	Personal consumption expenditures: Durable goods (chain-type price index)		6
114	DSERRG3Q086SBEA	Personal consumption expenditures: Services (chain-type price index)		6
115	DNDGRG3Q086SBEA	Personal consumption expenditures: Nondurable goods (chain-type price index)		6
116	DHCERG3Q086SBEA	Personal consumption expenditures: Services: Household consumption expenditures (chain-type price index)		6
117	DMOTRG3Q086SBEA	Personal consumption expenditures: Durable goods: Motor vehicles and parts (chain-type price index)		6
118	DFDHRG3Q086SBEA	Personal consumption expenditures: Durable goods: Furnishings and durable household equipment (chain-type price index)		6
119	DREQRG3Q086SBEA	Personal consumption expenditures: Durable goods: Recreational goods and vehicles (chain-type price index)		6
120	DODGRG3Q086SBEA	Personal consumption expenditures: Durable goods: Other durable goods (chain-type price index)		6
121	DFXARG3Q086SBEA	Personal consumption expenditures: Nondurable goods: Food and beverages purchased for off-premises consumption (chain-type price index)		6
122	DCLORG3Q086SBEA	Personal consumption expenditures: Nondurable goods: Clothing and footwear (chain-type price index)		6
123	DGOERG3Q086SBEA	Personal consumption expenditures: Nondurable goods: Gasoline and other energy goods (chain-type price index)		6
124	DONGRG3Q086SBEA	Personal consumption expenditures: Nondurable goods: Other nondurable goods (chain-type price index)		6
125	DHUTRG3Q086SBEA	Personal consumption expenditures: Services: Housing and utilities (chain-type price index)		6
126	DHLCRG3Q086SBEA	Personal consumption expenditures: Services: Health care (chain-type price index)		6

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel F: Prices (Continued)		
127	DTRSRG3Q086SBEA	Personal consumption expenditures: Transportation services (chain-type price index)		6
128	DRCARG3Q086SBEA	Personal consumption expenditures: Recreation services (chain-type price index)		6
129	DFSARG3Q086SBEA	Personal consumption expenditures: Services: Food services and accommodations (chain-type price index)		6
130	DIFSRG3Q086SBEA	Personal consumption expenditures: Financial services and insurance (chain-type price index)		6
131	DOTSRG3Q086SBEA	Personal consumption expenditures: Other services (chain-type price index)		6
132	CPIAUCSL	Consumer price index for all urban consumers: All items	Index 1982-84=100	6
133	CPILFESL	Consumer price index for all urban consumers: All items less food and energy	Index 1982-84=100	6
134	WPSFD49207	Producer price index by commodity for finished goods	Index 1982=100	6
135	PPIACO	Producer price index for all commodities	Index 1982=100	6
136	WPSFD49502	Producer price index by commodity for finished consumer goods	Index 1982=100	6
137	WPSFD4111	Producer price index by commodity for finished consumer foods	Index 1982=100	6
138	PPIIDC	Producer price index by commodity industrial commodities	Index 1982=100	6
139	WPSID61	Producer price index by commodity intermediate materials: Supplies and components	Index 1982=100	6
140	WPU0531	Producer price index by commodity for fuels and related products and power: Natural gas	Index 1982=100	5
141	WPU0561	Producer price index by commodity for fuels and related products and power: Crude petroleum (domestic production)	Index 1982=100	5
142	OILPRICEx	Real crude oil prices: West Texas Intermediate (WTI) - Cushing, Oklahoma	2017 USD per barrel	5
143	WPSID62	Producer price index: Crude materials for further processing	Index 1982=100	6
144	PPICMM	Producer price index: Commodities: Metals and metal products: Primary nonferrous metals	Index 1982=100	6
145	CPIAPPSL	Consumer price index for all urban consumers: Apparel	Index 1982-84=100	6
146	CPITRNSL	Consumer price index for all urban consumers: Transportation	Index 1982-84=100	6
147	CPIMEDSL	Consumer price index for all urban consumers: Medical Care	Index 1982-84=100	6
148	CUSR0000SAC	Consumer price index for all urban consumers: Commodities	Index 1982-84=100	6
149	CUSR0000SAD	Consumer price index for all urban consumers: Durables	Index 1982-84=100	6
150	CUSR0000SAS	Consumer price index for all urban consumers: Services	Index 1982-84=100	6
151	CPIULFSL	Consumer price index for all urban consumers: All items less food	Index 1982-84=100	6
152	CUSR0000SA0L2	Consumer price index for all urban consumers: All items less shelter	Index 1982-84=100	6
153	CUSR0000SA0L5	Consumer price index for all urban consumers: All items less medical care	Index 1982-84=100	6

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel G: Earnings and Productivity		
154	AHETPIx	Real average hourly earnings of production and nonsupervisory employees: Total private	2017 USD per hour	5
155	CES2000000008x	Real average hourly earnings of production and nonsupervisory employees: Construction	2017 USD per hour	5
156	CES3000000008x	Real average hourly earnings of production and nonsupervisory employees: Manufacturing	2017 USD per hour	5
157	COMPRNFB	Nonfarm business sector: Real compensation per hour	Index 2017=100	5
158	RCPHBS	Business sector: Real compensation per hour	Index 2017=100	5
159	OPHNFB	Nonfarm business sector: Real output per hour of all persons	Index 2017=100	5
160	OPHPBS	Business sector: Real output per hour of all persons	Index 2017=100	5
161	ULCBS	Business sector: Unit labor cost	Index 2017=100	5
162	ULCNFB	Nonfarm business sector: Unit labor cost	Index 2017=100	5
163	UNLPNBS	Nonfarm business sector: Unit nonlabor payments	Index 2017=100	5
164	CES0600000008	Average hourly earnings of production and nonsupervisory employees: Goods-producing	USD per hour	6
		Panel H: Money and Credit		
165	BOGMBASEREALx	St. Louis adjusted monetary base	Billions of 1982-84 USD	5
166	M1REAL	Real M1 money stock	Billions of 1982-84 USD	5
167	M2REAL	Real M2 money stock	Billions of 1982-84 USD	5
168	BUSLOANSx	Real commercial and industrial loans, all commercial banks	Billions of 2017 USD	5
169	CONSUMERx	Real consumer loans at all commercial banks	Billions of 2017 USD	5
170	NONREVSLx	Total real nonrevolving credit owned and securitized, outstanding	Billions of USD	5
171	REALLNx	Real real estate loans, all commercial banks	Billions of 2017 USD	5
172	REVOLSLx	Total real revolving credit owned and securitized, outstanding	Billions of 2017 USD	5
173	TOTALSLx	Total consumer credit outstanding	Billions of 2017 USD	5
174	TOTRESNS	Total reserves of depository institutions	Billions of USD	6
175	NONBORRES	Reserves of depository institutions, nonborrowed	Millions of USD	7
176	DTCOLNVHFNM	Consumer motor vehicle loans outstanding owned by finance companies	Millions of USD	6
177	DTCTHFNM	Total consumer loans and leases outstanding owned and securitized by finance companies	Millions of USD	6
178	INVEST	Securities in bank credit at all commercial banks	Billions of USD	6

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Table IA.III (Continued)

ID	Name	Description	Units	tcode
		Panel I: Consumer Sentiment		
179	UMCSENTx	University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	1
		Panel J: Non-Household Balance Sheets		
180	GFDEGDQ188S	Federal debt: Total public debt as percent of GDP	Percent	2
181	GFDEBTNx	Real federal debt: Total public debt	Millions of 2017 USD	2
182	TLBSNNCBx	Real nonfinancial corporate business sector liabilities	Billions of 2017 USD	5
183	TLBSNNCBBDIx	Nonfinancial corporate business sector liabilities to disposable business income	Percent	1
184	TTAABSNNCBx	Real nonfinancial corporate business sector assets	Billions of 2017 USD	5
185	TNWMVBSNNCBx	Real nonfinancial corporate business sector net worth	Billions of 2017 USD	5
186	TNWMVBSNNCBBDIx	Nonfinancial corporate business sector net worth to disposable business income	Percent	2
187	TLBSNNBx	Real nonfinancial noncorporate business sector liabilities	Billions of 2017 USD	5
188	TLBSNNBBDIx	Nonfinancial noncorporate business sector liabilities to disposable business income	Percent	1
189	TABSNNBx	Real nonfinancial noncorporate business sector assets	Billions of 2017 USD	5
190	TNWBSNNBx	Real nonfinancial noncorporate business sector net worth	Billions of 2017 USD	5
191	TNWBSNNBBDIx	Nonfinancial noncorporate business sector net worth to disposable business income	Percent	2
192	CNCFx	Real disposable business income (corporate cash flow with IVA minus taxes on corporate income)	Billions of 2017 USD	5

Table IA.IV: Diagnostics for Selecting the RP-PCA Penalty Parameter

The table reports model diagnostics from the first and second stages of the Giglio and Xiu (2021) procedure applied to a cross section of 865 equity portfolios. We estimate $K = 6$ latent factors based on the RP-PCA method of Lettau and Pelger (2020a,b) and report results for various values of the RP-PCA penalty parameter (ω). For each model, the table presents the implied annualized Sharpe ratio of the tangency portfolio spanned by the linear combination of the K latent factors, the average ratio of idiosyncratic variance to total variance, the root-mean-square pricing error (in percent per year) from the time-series regressions, the cross-sectional R^2 value, and the average absolute pricing error (in percent per year) from the cross-sectional regression.

		First stage (Time-series regressions)		Second stage (Cross-sectional regressions)	
Penalty ω	Sharpe ratio $SR(\omega)$	Idiosyncratic variance $\mathbb{A}[\widehat{\sigma}^2_{e,n}/\widehat{\sigma}^2_n]$ (%)	Pricing errors $(\mathbb{A}[\widehat{\alpha}^2_n])^{1/2}$ (%)	Overall model fit R^2 (%)	Pricing errors $\mathbb{A}[\lvert\widehat{a}_n\rvert]$ (%)
−1	0.88	7.41	1.71	35.49	1.23
0	1.03	7.42	1.69	60.16	0.96
5	1.52	7.47	1.81	97.42	0.29
10	1.67	7.48	1.87	99.30	0.16
20	1.76	7.50	1.90	99.82	0.08
30	1.80	7.50	1.91	99.92	0.05
40	1.81	7.50	1.92	99.96	0.04
50	1.83	7.50	1.92	99.97	0.03

Table IA.V: Spanning Regressions for Latent PCA Factors

The table reports results from spanning regressions of latent factors on the market factor (Panel A), the six Fama-French (2016) factors (Panel B), and the four Hou-Xue-Zhang (2015) factors (Panel C). The six latent factors are extracted from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with penalty parameter $\omega = -1$. For each spanning regression, the table reports the annualized alpha, the factor loadings, and the regression R^2 value. The numbers in parentheses are Newey-West (1987) t-statistics based on a lag length equal to four. For the alpha and factor loading estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a two-tailed test.

Parameter	F_1	F_2	F_3	F_4	F_5	F_6
Panel A: CAPM Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	−0.15	0.17	1.63***	0.53*	0.62***	0.30
	(−0.25)	(0.30)	(3.03)	(1.95)	(2.82)	(1.52)
MKT loading, $\widehat{\beta}_k$	0.98***	0.04***	0.00	0.00	0.00	0.00
R^2 (%)	95.63	3.80	0.01	0.04	0.04	0.19
Panel B: Fama-French (2016) Six-Factor Model Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	−0.10	0.00	−0.40*	0.16	−0.19	−0.03
	(−0.51)	(−0.05)	(−1.90)	(0.81)	(−1.21)	(−0.15)
Factor loadings:						
MKT	0.90***	0.12***	0.07***	−0.01*	0.01***	0.02***
SMB	0.30***	−0.30***	−0.04***	0.08***	0.05***	−0.03***
HML	0.03***	−0.06***	0.13***	−0.03***	0.00	0.03***
RMW	−0.01	0.05***	0.20***	0.07***	−0.01	−0.05***
CMA	0.05***	−0.02	0.10***	−0.04***	0.04***	0.03
UMD	−0.04***	0.03***	0.01	0.05***	0.08***	0.03***
R^2 (%)	99.55	95.60	78.72	52.82	60.49	34.31
Panel C: Hou-Xue-Zhang (2015) q-Factor Model Regressions						
Intercept, $\widehat{\alpha}_k$ (%)	−0.04	−0.14	−0.60	0.14	0.04	0.14
	(−0.17)	(−0.75)	(−1.20)	(0.61)	(0.14)	(0.56)
Factor loadings:						
MKT	0.90***	0.13***	0.06***	−0.01*	0.00	0.02***
ME	0.29***	−0.30***	−0.01	0.07***	0.03**	−0.04***
ROE	−0.09***	0.12***	0.11***	0.10***	0.05***	−0.03*
IA	0.05**	−0.06***	0.26***	−0.07***	0.04	0.07***
R^2 (%)	99.38	92.90	48.02	39.90	14.03	20.42

Table IA.VI: Macroeconomic Factors with Statistically Insignificant Risk Premia

The table reports estimates of the risk premia for selected macroeconomic factors using the augmented three-pass approach of Giglio and Xiu (2021). The table focuses on macroeconomic factors with statistically insignificant risk premia. The latent factors are estimated from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the number of latent factors $K = 6$ and the RP-PCA penalty parameter $\omega = 10$. For each macroeconomic variable, the table reports the risk premium estimate, the corresponding asymptotic standard error and t-statistic, the R^2 value obtained from projecting the macroeconomic variable onto the K latent factors, the projected factor's annualized Sharpe ratio, and the p-value from a test of the null hypothesis that the factor is weak. The final column reports the Benjamini-Hochberg (1995) adjusted p-value for the risk premium estimate, which accounts for multiple testing across the full set of macroeconomic variables. The panels of the table are grouped by macroeconomic variable category.

	Three-pass estimation					Weak factor	FDR analysis
Variable	$\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	p-value	p_{BH}-value
Panel A: NIPA (18/22)							
EXPGSC1	0.344	0.212	1.62	4.56	0.81	0.05	0.41
B021RE1Q156NBEA	0.316	0.200	1.58	7.08	0.59	0.00	0.41
GCEC1	−0.265	0.183	−1.45	2.04	−0.93	0.37	0.51
OUTNFB	0.342	0.243	1.41	2.86	1.01	0.42	0.52
GDPC1	0.349	0.249	1.40	3.14	0.98	0.39	0.52
OUTBS	0.331	0.252	1.31	3.17	0.93	0.42	0.55
SLCEx	−0.263	0.211	−1.25	1.62	−1.03	0.64	0.56
PCNDx	0.257	0.207	1.24	2.90	0.75	0.22	0.56
FPIx	0.233	0.193	1.21	1.77	0.88	0.77	0.56
B020RE1Q156NBEA	0.210	0.192	1.09	5.07	0.47	0.08	0.60
GPDIC1	0.288	0.268	1.07	5.69	0.60	0.30	0.60
A823RL1Q225SBEA	−0.249	0.234	−1.07	2.57	−0.78	0.39	0.60
A014RE1Q156NBEA	0.195	0.326	0.60	11.64	0.29	0.05	0.76
FGRECPTx	0.105	0.337	0.31	2.83	0.31	0.06	0.88
DPIC96	0.069	0.233	0.30	1.29	0.30	0.94	0.88
PCDGx	0.060	0.272	0.22	6.29	0.12	0.00	0.92
PNFIx	−0.009	0.234	−0.04	1.98	−0.03	0.50	0.98
Y033RC1Q027SBEAx	−0.008	0.232	−0.04	2.11	−0.03	0.62	0.98
Panel B: Industrial Production (15/16)							
IPCONGD	0.302	0.184	1.64	3.58	0.80	0.33	0.41
IPDCONGD	0.243	0.186	1.30	2.21	0.81	0.59	0.55
IPFINAL	0.270	0.215	1.26	4.90	0.61	0.26	0.56
IPB51222S	0.188	0.180	1.04	6.66	0.36	0.00	0.61
INDPRO	0.207	0.206	1.01	3.57	0.55	0.32	0.62
IPMANSICS	0.191	0.197	0.97	3.45	0.51	0.30	0.64
TCU	0.213	0.256	0.83	5.33	0.46	0.04	0.71
IPB51110SQ	0.147	0.179	0.82	1.31	0.64	0.89	0.71
IPBUSEQ	0.174	0.218	0.80	5.42	0.37	0.08	0.71
IPDMAT	0.180	0.234	0.77	2.33	0.59	0.54	0.71
CUMFNS	0.149	0.237	0.63	4.54	0.35	0.19	0.76
IPMAT	0.130	0.218	0.60	2.43	0.42	0.48	0.76
IPB51220SQ	0.111	0.199	0.56	8.08	0.20	0.00	0.77
IPNMAT	−0.092	0.187	−0.49	1.73	−0.35	0.62	0.82
IPFUELS	−0.090	0.209	−0.43	2.87	−0.27	0.33	0.85

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Table IA.VI (Continued)

	Three-pass estimation					Weak factor	FDR analysis
Variable	$\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	p-value	p_{BH}-value
Panel C: Employment and Unemployment (26/49)							
UNRATE	−0.291	0.180	−1.61	4.38	−0.69	0.58	0.41
AWHNONAG	0.330	0.207	1.60	4.89	0.75	0.11	0.41
USLAH	0.214	0.136	1.58	4.62	0.50	0.61	0.41
CLAIMSx	−0.560	0.357	−1.57	7.26	−1.04	0.11	0.41
UNRATESTx	−0.228	0.148	−1.54	2.54	−0.72	0.84	0.43
LNS14000026	−0.229	0.161	−1.42	4.18	−0.56	0.67	0.52
NDMANEMP	0.249	0.187	1.33	4.16	0.61	0.51	0.55
LNS13023705	0.242	0.182	1.33	4.18	0.59	0.05	0.55
CES9091000001	−0.367	0.279	−1.32	6.16	−0.74	0.21	0.55
CES9093000001	0.193	0.159	1.21	3.55	0.51	0.14	0.56
CIVPART	0.204	0.186	1.10	5.51	0.44	0.16	0.60
USWTRADE	0.207	0.191	1.08	3.41	0.56	0.10	0.60
USGOOD	0.249	0.231	1.08	3.34	0.68	0.71	0.60
AWOTMAN	0.222	0.218	1.02	1.14	1.04	0.65	0.62
MANEMP	0.225	0.225	1.00	3.19	0.63	0.82	0.62
UEMPLT5	−0.205	0.206	−1.00	1.38	−0.87	0.75	0.62
LNS13023557	−0.182	0.199	−0.91	1.43	−0.76	0.73	0.67
UNRATELTx	−0.262	0.291	−0.90	4.22	−0.64	0.16	0.67
UEMP15T26	−0.181	0.206	−0.88	2.16	−0.62	0.79	0.68
DMANEMP	0.209	0.240	0.87	2.52	0.66	0.90	0.68
USGOVT	0.126	0.166	0.76	4.67	0.29	0.22	0.71
CES9092000001	0.143	0.219	0.65	3.06	0.41	0.56	0.76
UEMP27OV	0.099	0.239	0.41	2.24	0.33	0.35	0.85
UEMPMEAN	0.069	0.250	0.28	1.94	0.25	0.16	0.89
LNS13023569	−0.041	0.237	−0.17	0.33	−0.36	0.97	0.93
USMINE	−0.018	0.297	−0.06	1.65	−0.07	0.39	0.98
Panel D: Housing (0/11)							
< None >							
Panel E: Inventories, Orders, and Sales (8/8)							
INVCQRMTSPL	0.417	0.322	1.29	16.19	0.52	0.00	0.55
CMRMTSPLx	0.267	0.212	1.26	2.24	0.89	0.39	0.56
BUSINVx	0.260	0.239	1.09	7.20	0.48	0.01	0.60
RSAFSx	0.290	0.268	1.08	6.23	0.58	0.00	0.60
ANDENOx	−0.177	0.242	−0.73	3.18	−0.50	0.19	0.73
AMDMNOx	0.093	0.215	0.43	2.61	0.29	0.35	0.85
ISRATIOx	−0.058	0.196	−0.30	4.32	−0.14	0.05	0.88
AMDMUOx	−0.051	0.247	−0.21	4.30	−0.12	0.00	0.92

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Table IA.VI (Continued)

Variable	Three-pass estimation $\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	Weak factor p-value	FDR analysis p_{BH}-value
Panel F: Prices (44/47)							
DDURRG3Q086SBEA	−0.283	0.200	−1.42	1.89	−1.03	0.51	0.52
CPILFESL	−0.298	0.239	−1.25	11.54	−0.44	0.02	0.56
DHLCRG3Q086SBEA	−0.239	0.201	−1.19	5.75	−0.50	0.02	0.57
PCEPILFE	−0.237	0.208	−1.14	3.88	−0.60	0.08	0.59
WPU0561	0.260	0.261	1.00	9.80	0.42	0.00	0.62
DHUTRG3Q086SBEA	0.193	0.207	0.93	2.40	0.62	0.46	0.66
OILPRICEx	0.209	0.229	0.91	12.02	0.30	0.00	0.67
DFSARG3Q086SBEA	0.173	0.199	0.87	3.38	0.47	0.24	0.68
PPIACO	−0.196	0.250	−0.79	7.36	−0.36	0.00	0.71
DTRSRG3Q086SBEA	0.115	0.147	0.78	3.33	0.31	0.00	0.71
WPSFD4111	−0.183	0.252	−0.73	3.25	−0.51	0.05	0.73
CUSR0000SA0L5	−0.183	0.257	−0.71	8.54	−0.31	0.00	0.74
GPDICTPI	0.235	0.351	0.67	5.87	0.49	0.32	0.76
DRCARG3Q086SBEA	−0.122	0.189	−0.65	3.77	−0.31	0.15	0.76
DIFSRG3Q086SBEA	−0.121	0.191	−0.63	1.81	−0.45	0.88	0.76
CPIAUCSL	−0.160	0.263	−0.61	9.04	−0.27	0.00	0.76
WPSID62	−0.156	0.260	−0.60	7.15	−0.29	0.05	0.76
CPIULFSL	−0.152	0.261	−0.58	8.07	−0.27	0.00	0.76
CUSR0000SAS	−0.134	0.240	−0.56	7.91	−0.24	0.01	0.77
IPDBS	0.135	0.263	0.51	4.38	0.32	0.01	0.81
DODGRG3Q086SBEA	−0.099	0.202	−0.49	3.69	−0.26	0.02	0.82
PCECTPI	−0.113	0.267	−0.42	8.03	−0.20	0.00	0.85
CUSR0000SAC	−0.121	0.288	−0.42	7.42	−0.22	0.02	0.85
PPIIDC	−0.113	0.270	−0.42	6.53	−0.22	0.01	0.85
DHCERG3Q086SBEA	−0.080	0.204	−0.39	2.62	−0.25	0.19	0.87
CUSR0000SA0L2	−0.098	0.263	−0.37	7.97	−0.17	0.00	0.88
PPICMM	−0.097	0.271	−0.36	8.55	−0.17	0.01	0.88
WPSID61	−0.083	0.239	−0.35	5.55	−0.18	0.01	0.88
DONGRG3Q086SBEA	−0.100	0.290	−0.35	5.15	−0.22	0.03	0.88
DREQRG3Q086SBEA	0.079	0.235	0.34	0.76	0.46	0.71	0.88
DSERRG3Q086SBEA	−0.065	0.197	−0.33	2.68	−0.20	0.15	0.88
DGDSRG3Q086SBEA	−0.093	0.301	−0.31	7.60	−0.17	0.00	0.88
DGOERG3Q086SBEA	0.097	0.324	0.30	6.19	0.20	0.03	0.88
CPITRNSL	−0.085	0.285	−0.30	6.50	−0.17	0.06	0.88
DFDHRG3Q086SBEA	−0.050	0.206	−0.24	2.40	−0.16	0.18	0.91
WPSFD49502	−0.059	0.248	−0.24	8.91	−0.10	0.00	0.91
DOTSRG3Q086SBEA	−0.043	0.194	−0.22	1.65	−0.17	0.52	0.92
CPIMEDSL	0.040	0.213	0.19	9.03	0.07	0.05	0.93
GDPCTPI	−0.052	0.284	−0.18	5.03	−0.11	0.02	0.93
WPSFD49207	−0.038	0.249	−0.15	8.47	−0.07	0.00	0.94
CPIAPPSL	−0.017	0.177	−0.10	3.29	−0.05	0.27	0.98
DFXARG3Q086SBEA	−0.022	0.288	−0.08	2.11	−0.08	0.38	0.98
DNDGRG3Q086SBEA	−0.018	0.313	−0.06	7.78	−0.03	0.00	0.98
DCLORG3Q086SBEA	0.009	0.184	0.05	2.87	0.03	0.41	0.98

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Table IA.VI (Continued)

Variable	Three-pass estimation $\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	Weak factor p-value	FDR analysis p_{BH}-value
Panel G: Earnings and Productivity (9/11)							
CES0600000008	−0.388	0.300	−1.29	2.83	−1.15	0.44	0.55
CES2000000008x	−0.237	0.207	−1.14	0.98	−1.19	0.87	0.59
AHETPIx	−0.158	0.170	−0.93	1.94	−0.57	0.92	0.66
UNLPNBS	0.227	0.251	0.90	2.64	0.70	0.42	0.67
CES3000000008x	−0.167	0.236	−0.70	2.03	−0.58	0.71	0.74
OPHNFB	−0.165	0.251	−0.66	7.56	−0.30	0.23	0.76
OPHPBS	−0.172	0.264	−0.65	6.63	−0.33	0.32	0.76
ULCNFB	−0.068	0.254	−0.27	4.58	−0.16	0.19	0.90
ULCBS	−0.048	0.266	−0.18	4.50	−0.11	0.26	0.93
Panel H: Money and Credit (13/14)							
BOGMBASEREALx	−0.194	0.145	−1.34	4.22	−0.47	0.11	0.55
DTCTHFNM	−0.285	0.228	−1.25	1.89	−1.04	0.14	0.56
REALLNx	0.240	0.198	1.21	4.26	0.58	0.01	0.56
TOTRESNS	0.381	0.330	1.16	7.89	0.68	0.56	0.59
NONBORRES	0.324	0.297	1.09	3.48	0.87	0.70	0.60
TOTALSLx	0.232	0.223	1.04	1.69	0.89	0.47	0.61
M1REAL	−0.104	0.128	−0.81	4.97	−0.23	0.43	0.71
NONREVSLx	0.137	0.179	0.77	0.77	0.78	0.81	0.71
CONSUMERx	−0.207	0.339	−0.61	4.74	−0.47	0.38	0.76
INVEST	0.113	0.192	0.59	5.93	0.23	0.08	0.76
REVOLSLx	−0.015	0.120	−0.12	2.62	−0.05	0.61	0.96
BUSLOANSx	−0.013	0.226	−0.06	2.01	−0.05	0.09	0.98
M2REAL	0.001	0.201	0.00	8.37	0.00	0.00	1.00
Panel I: Consumer Sentiment (1/1)							
UMCSENTx	0.253	0.213	1.19	9.85	0.40	0.00	0.57
Panel J: Non-Household Balance Sheets (12/13)							
GFDEGDQ188S	−0.298	0.185	−1.61	4.98	−0.67	0.05	0.41
GFDEBTNx	−0.172	0.150	−1.15	5.52	−0.37	0.02	0.59
TTAABSNNCBx	0.293	0.357	0.82	4.42	0.70	0.22	0.71
TNWMVBSNNCBBDIx	0.180	0.231	0.78	7.78	0.32	0.00	0.71
TLBSNNCBx	−0.217	0.283	−0.77	10.54	−0.33	0.00	0.71
TLBSNNBBDIx	−0.126	0.186	−0.68	2.93	−0.37	0.19	0.76
TABSNNBx	0.155	0.243	0.64	1.26	0.69	0.72	0.76
TNWBSNNBx	0.153	0.255	0.60	1.25	0.69	0.78	0.76
TLBSNNBx	0.088	0.284	0.31	2.65	0.27	0.58	0.88
CNCFx	0.014	0.217	0.07	3.29	0.04	0.16	0.98
TLBSNNCBBDIx	−0.009	0.201	−0.05	5.35	−0.02	0.00	0.98
TNWBSNNBBDIx	0.004	0.218	0.02	3.33	0.01	0.15	0.99

Table IA.VII: Macroeconomic Factors with Statistically Significant Risk Premia: PCA Factor Estimation
The table reports estimates of the risk premia for selected macroeconomic factors using the augmented three-pass approach of Giglio and Xiu (2021). The table focuses on macroeconomic factors with statistically significant risk premia. The latent factors are estimated from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the number of latent factors $K = 6$ and the RP-PCA penalty parameter $\omega = -1$. For each macroeconomic variable, the table reports the risk premium estimate, the corresponding asymptotic standard error and t-statistic, the R^2 value obtained from projecting the macroeconomic variable onto the K latent factors, the projected factor's annualized Sharpe ratio, and the p-value from a test of the null hypothesis that the factor is weak. The final column reports the Benjamini-Hochberg (1995) adjusted p-value for the risk premium estimate, which accounts for multiple testing across the full set of macroeconomic variables. For the risk premium estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a two-tailed test. The panels of the table are grouped by macroeconomic variable category.

	Three-pass estimation					Weak factor	FDR analysis
Variable	$\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	p-value	p_{BH}-value
			Panel A: NIPA (7/22)				
PRFIx	0.328**	0.140	2.34	7.42	0.60	0.00	0.33
PCESVx	0.267*	0.139	1.92	5.33	0.58	0.23	0.44
FPIx	0.221*	0.117	1.88	2.53	0.69	0.50	0.44
SLCEx	−0.220*	0.119	−1.85	2.94	−0.64	0.22	0.44
EXPGSC1	0.228*	0.131	1.74	5.12	0.50	0.04	0.45
GCEC1	−0.180*	0.105	−1.72	2.65	−0.55	0.20	0.45
PCNDx	0.192*	0.114	1.68	3.33	0.53	0.22	0.46
			Panel B: Industrial Production (0/16)				
			< None >				
			Panel C: Employment and Unemployment (15/49)				
USPBS	0.288**	0.125	2.31	8.21	0.50	0.05	0.33
HWIURATIOx	0.280**	0.123	2.28	4.88	0.63	0.07	0.33
LNS12032194	−0.266**	0.120	−2.22	6.03	−0.54	0.16	0.33
USFIRE	0.260**	0.119	2.18	4.36	0.62	0.38	0.33
UEMP5TO14	−0.199**	0.093	−2.13	3.88	−0.51	0.25	0.33
AWHMAN	0.244**	0.115	2.12	3.32	0.67	0.19	0.33
LNS13023621	−0.217**	0.109	−2.00	5.44	−0.47	0.20	0.39
LNS14000012	−0.185*	0.099	−1.88	2.88	−0.55	0.42	0.44
CES0600000007	0.225*	0.121	1.86	2.57	0.70	0.20	0.44
AWHNONAG	0.225*	0.124	1.82	4.94	0.51	0.10	0.44
CLAIMSx	−0.409*	0.233	−1.75	7.94	−0.73	0.04	0.45
HOANBS	0.229*	0.133	1.72	5.75	0.48	0.30	0.45
USSERV	0.163*	0.095	1.71	6.10	0.33	0.56	0.45
HOABS	0.223*	0.133	1.68	5.67	0.47	0.27	0.46
LNS14000025	−0.197*	0.118	−1.67	5.85	−0.41	0.35	0.46

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Table IA.VII (Continued)

Variable	Three-pass estimation: $\widehat{\lambda}_j^G$	$\sigma(\widehat{\lambda}_j^G)$	$t(\widehat{\lambda}_j^G)$	R^2 (%)	Sharpe	Weak factor: p-value	FDR analysis: p_{BH}-value
Panel D: Housing (11/11)							
HOUST	0.396***	0.123	3.21	7.41	0.73	0.01	0.20
HOUSTS	0.360***	0.124	2.91	6.47	0.71	0.05	0.20
HOUSTMW	0.366***	0.127	2.89	7.20	0.68	0.01	0.20
HOUSTW	0.353***	0.126	2.79	6.30	0.70	0.01	0.20
HOUSTNE	0.396***	0.153	2.59	6.42	0.78	0.05	0.30
PERMITNE	0.298**	0.122	2.44	7.98	0.53	0.06	0.33
PERMIT	0.314**	0.132	2.38	6.97	0.60	0.03	0.33
PERMITW	0.347**	0.147	2.36	6.04	0.71	0.12	0.33
HOUST5F	0.303**	0.135	2.24	4.25	0.73	0.34	0.33
PERMITS	0.310**	0.145	2.14	6.93	0.59	0.03	0.33
PERMITMW	0.245**	0.120	2.04	7.25	0.46	0.00	0.38
Panel E: Inventories, Orders, and Sales (0/8)							
< None >							
Panel F: Prices (3/47)							
CUSR0000SAD	−0.339**	0.133	−2.55	5.65	−0.71	0.01	0.30
CPILFESL	−0.313*	0.167	−1.88	11.69	−0.46	0.01	0.44
DHLCRG3Q086SBEA	−0.244*	0.134	−1.82	5.89	−0.50	0.01	0.44
Panel G: Earnings and Productivity (2/11)							
COMPRNFB	−0.211*	0.122	−1.73	10.31	−0.33	0.01	0.45
RCPHBS	−0.199*	0.121	−1.65	10.13	−0.31	0.01	0.46
Panel H: Money and Credit (1/14)							
DTCOLNVHFNM	−0.268*	0.151	−1.77	3.76	−0.69	0.09	0.45
Panel I: Consumer Sentiment (1/1)							
UMCSENTx	0.276**	0.129	2.14	11.58	0.41	0.00	0.33
Panel J: Non-Household Balance Sheets (1/13)							
TNWMVBSNNCBx	0.532***	0.190	2.80	28.82	0.50	0.00	0.20

Table IA.VIII: Comparison of Risk Premium Estimation Methods

The table summarizes the risk premia estimation results from the augmented three-pass approach of Giglio and Xiu (2021) and the standard two-pass approach across 192 macroeconomic factors. Under the augmented Giglio and Xiu (2021) approach, the latent factors are estimated from a cross section of 865 equity portfolios using the RP-PCA method of Lettau and Pelger (2020a,b) with the number of latent factors $K = 6$ and the RP-PCA penalty parameter $\omega = 10$. The risk premium for a given macroeconomic factor is estimated by combining the second-pass estimates of the latent factor risk prices with the third-pass estimates of the macroeconomic factor's loadings on the latent factors. We consider a version of the two-pass procedure that controls for *MKT* and a version that controls for *MKT*, *SMB*, and *HML* (FF3 controls). For the two-pass models in Panel A (Panel B), the test assets are 865 portfolios from Kenneth French and OSAP (30 decile portfolios formed from univariate sorts on size, book-to-market equity, and momentum). For each macroeconomic variable category and estimation approach, the table reports the number macroeconomic factors with statistically significant risk premia at the 10% level. The table also reports, for each category and two-pass specification, the median ratio of the absolute risk premium estimate from the two-pass approach to the absolute risk premium estimate from the augmented Giglio and Xiu (2021) approach. In the two-pass estimation approach, we restrict the intercept in the second-pass regression to be zero and assess statistical significance using Shanken (1992) standard errors.

		Augmented GX procedure	Two-pass procedure, *MKT* control		Two-pass procedure, FF3 controls	
Category	Total factors	Sig. factors	Sig. factors	$\mathbb{M}[\lvert\widehat{\lambda}_j^{TP}\rvert/\lvert\widehat{\lambda}_j^{GX}\rvert]$	Sig. factors	$\mathbb{M}[\lvert\widehat{\lambda}_j^{TP}\rvert/\lvert\widehat{\lambda}_j^{GX}\rvert]$
Panel A: 865 Test Portfolios (315 Kenneth French Portfolios and 550 OSAP Portfolios)						
All	192	46	107	7.0	137	4.9
NIPA	22	4	10	5.8	15	3.7
Industrial Production	16	1	4	5.6	6	2.1
Employment and Unemployment	49	23	37	6.9	38	3.4
Housing	11	11	10	6.3	10	4.1
Inventories, Orders, and Sales	8	0	3	5.6	5	10.5
Prices	47	3	21	7.1	37	15.1
Earnings and Productivity	11	2	7	16.8	11	9.2
Money and Credit	14	1	7	9.7	5	5.7
Consumer Sentiment	1	0	0	0.8	1	3.5
Non-Household Balance Sheets	13	1	8	12.1	9	9.8

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Table IA.VIII (Continued)

Category	Total factors	Augmented GX procedure	Two-pass procedure, *MKT* control		Two-pass procedure, FF3 controls	
		Sig. factors	Sig. factors	$\mathbb{M}[\lvert\widehat{\lambda}_j^{TP}\rvert/\lvert\widehat{\lambda}_j^{GX}\rvert]$	Sig. factors	$\mathbb{M}[\lvert\widehat{\lambda}_j^{TP}\rvert/\lvert\widehat{\lambda}_j^{GX}\rvert]$
Panel B: 30 Test Portfolios from Liu and Zhang (2008)						
All	192	46	135	16.0	167	23.1
NIPA	22	4	20	18.0	21	24.0
Industrial Production	16	1	15	23.9	14	25.9
Employment and Unemployment	49	23	45	15.2	46	15.9
Housing	11	11	10	10.2	11	12.3
Inventories, Orders, and Sales	8	0	5	13.2	6	23.0
Prices	47	3	15	17.0	39	45.7
Earnings and Productivity	11	2	8	15.9	8	22.8
Money and Credit	14	1	9	16.4	11	25.6
Consumer Sentiment	1	0	0	5.5	1	9.7
Non-Household Balance Sheets	13	1	8	21.3	10	25.7

Table IA.IX: Long-Short Portfolios with Statistically Insignificant CAPM Alphas

The table reports average returns and parameter estimates from CAPM regressions for long-short tercile portfolios sorted on various firm characteristics. The average returns and alphas are reported in percent per year. The t-statistics for the average returns and CAPM regression parameters are constructed following the approach in Newey and West (1987) based on a lag length equal to four. The table includes results for the 45 of the 149 long-short portfolios with statistically insignificant CAPM alphas at the 5% level. For the average return and alpha estimates, a "***" ("**") ["*"] denotes significance at the 1% (5%) [10%] level using a one-tailed test. The panels of the table are grouped by anomaly variable category.

	Average returns		CAPM regressions				
Anomaly	$\overline{R}_i$ (%)	$t(\overline{R}_i)$	$\widehat{\alpha}_i^C$ (%)	$t(\widehat{\alpha}_i^C)$	$\widehat{\beta}_i$ (%)	$t(\widehat{\beta}_i)$	R^2 (%)
Panel A: Momentum							
ret_3_1	0.85	0.63	1.92*	1.58	−0.14	−2.30	4.09
Panel B: Value							
at_me	2.65	1.10	3.99*	1.56	−0.17	−1.70	4.00
debt_me	1.03	0.46	2.56	1.03	−0.20	−1.85	5.55
Panel C: Investment							
col_gr1a	0.15	0.11	1.90*	1.35	−0.23	−3.88	17.74
ncol_gr1a	0.57	0.81	−0.05	−0.08	0.08	4.52	9.78
ni_ar1	0.23	0.51	−0.08	−0.18	0.04	2.72	4.20
saleq_gr1	1.15	0.70	2.69*	1.53	−0.20	−2.49	9.14
seas_16_20na	0.66	0.86	1.26*	1.44	−0.08	−2.14	4.69
Panel D: Profitability							
at_turnover	2.75***	2.45	1.76*	1.39	0.13	3.14	6.62
dgp_dsale	0.99*	1.44	0.87*	1.29	0.02	0.53	0.25
dolvol_var_126d	0.18	0.15	0.92	0.78	−0.10	−3.15	5.46
dsale_drec	−0.98	−1.72	−0.87	−1.40	−0.01	−0.57	0.35
dsale_dsga	−0.24	−0.30	−0.27	−0.32	0.00	0.12	0.02
gp_atl1	1.93*	1.40	0.35	0.24	0.21	3.97	12.18
ni_inc8q	0.27	0.30	0.66	0.73	−0.05	−1.28	1.81
op_atl1	2.31**	1.87	1.93*	1.49	0.05	1.18	0.93
opex_at	2.70***	2.45	1.46	1.23	0.16	4.77	11.08
sale_emp_gr1	0.24	0.34	−0.13	−0.17	0.05	1.39	2.56
saleq_su	0.44	0.49	0.21	0.21	0.03	0.66	0.62
tax_gr1a	0.90	1.06	0.33	0.38	0.07	1.92	3.62
turnover_var_126d	0.47	0.41	1.01	0.86	−0.07	−2.40	3.10
Panel E: Intangibles							
age	−1.84	−0.81	−5.46	−2.50	0.47	5.64	31.36
aliq_mat	−3.64	−2.36	−4.26	−2.42	0.08	1.22	1.96
at_be	−1.70	−0.95	−2.75	−1.32	0.14	1.61	4.30
bidaskhl_21d	−2.49	−1.00	−6.81	−2.84	0.56	6.01	34.06
cash_at	1.74	0.80	−0.83	−0.37	0.33	3.34	17.10
coskew_21d	1.10	1.19	1.52*	1.53	−0.05	−1.66	2.16
kz_index	−1.24	−1.11	−0.77	−0.62	−0.06	−1.20	1.73
netdebt_me	0.71	0.35	−0.98	−0.46	0.22	2.30	8.29
ni_ivol	−0.69	−0.40	−3.46	−2.03	0.36	6.59	26.00
pi_nix	0.48	0.65	0.15	0.19	0.04	1.46	2.01
rd5_at	2.97	1.27	0.83	0.37	0.28	3.65	12.51

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Table IA.IX (Continued)

Anomaly	Average returns		CAPM regressions				
	$\overline{R}_i$ (%)	$t(\overline{R}_i)$	$\widehat{\alpha}_i^C$ (%)	$t(\widehat{\alpha}_i^C)$	$\widehat{\beta}_i$ (%)	$t(\widehat{\beta}_i)$	R^2 (%)
Panel E: Intangibles (Continued)							
rd_sale	1.02	0.35	−1.82	−0.61	0.37	2.91	12.79
sti_gr1a	−0.45	−0.77	−0.49	−0.73	0.00	0.17	0.03
tangibility	1.95*	1.58	1.79*	1.38	0.02	0.35	0.21
z_score	−0.15	−0.08	−1.74	−0.88	0.21	2.48	9.12
Panel F: Trading Frictions							
ami_126d	0.14	0.11	−1.05	−0.83	0.16	4.76	8.08
dolvol_126d	0.80	0.65	0.80	0.63	0.00	−0.01	0.00
earnings_variability	0.59	0.66	1.52*	1.59	−0.12	−2.69	9.88
iskew_capm_21d	0.44	0.92	0.73*	1.50	−0.04	−2.03	3.63
iskew_ff3_21d	−0.11	−0.23	0.09	0.18	−0.03	−1.61	1.81
iskew_hxz4_21d	−0.19	−0.38	0.02	0.05	−0.03	−1.56	1.93
market_equity	0.65	0.42	−1.30	−0.83	0.25	6.45	14.45
prc	−0.05	−0.03	−2.56	−1.44	0.33	5.00	17.21
zero_trades_21d	−1.33	−0.75	2.15*	1.42	−0.45	−7.78	41.86

Table IA.X: Performance of Two-Factor Models with Macroeconomic Factors: Robustness Tests

The table summarizes the performance of various two-factor models in explaining the average returns for the 104 of the 149 long-short tercile portfolios with statistically significant CAPM alphas at the 5% level. The results in Panel A correspond to our base case design, and those in Panels B–D correspond to alternative designs as described in the table. For each design, the table reports the number macroeconomic factors with statistically significant risk premia estimated using the augmented three-pass approach of Giglio and Xiu (2021), the minimum number of alpha estimates that are statistically significant across the two-factor models (i.e., models that include the market factor and a mimicking portfolio for one of the significant macroeconomic factors), the two-factor model(s) that provides the minimum number of alpha estimates that are statistically significant, the maximum average percentage reduction in the CAPM alpha across the two-factor models, and the two-factor model that provides the maximum average CAPM alpha reduction.

		Significant anomalies		Average $\widehat{\alpha}_i^C$ reduction (%)	
Description	Sig. factors	Minimum	Minimum ID(s)	Maximum	Maximum ID
Panel A: Base Case					
Base case design	46	33	HOUST	61.4	HOUST
Panel B: RP-PCA Penalty Parameter					
$\omega = -1$ (PCA)	41	55	DTCOLNVHFNM	44.1	DTCOLNVHFNM
$\omega = 0$	45	50	DTCOLNVHFNM	48.8	DTCOLNVHFNM
$\omega = 5$	50	37	HOUST	59.5	HOUST
$\omega = 20$	43	32	PCESVx, HOUSTMW	62.3	HOUST
$\omega = 30$	39	32	PCESVx, HOUSTMW	62.5	HOUST
$\omega = 40$	38	30	PCESVx	62.7	HOUST
$\omega = 50$	38	30	PCESVx, HOUSTMW	62.7	HOUST
Panel C: Number of Latent Factors					
$K = 3$	25	51	USFIRE	45.4	HOUST
$K = 4$	34	34	HOUSTMW	60.0	HOUST
$K = 5$	44	33	HOUSTMW	60.3	HOUST
$K = 7$	24	40	DMOTRG3Q086SBEA, OPHNFB	55.4	USSERV
$K = 13$	43	44	HOUSTMW	50.9	HOUSTMW
Panel D: Basis Assets for RP-PCA Estimation					
315 Kenneth French portfolios	48	38	DTCOLNVHFNM	54.9	USFIRE
550 OSAP portfolios	21	35	HOUSTMW	63.8	HOUSTMW