Common Risk Factors in the Returns on Stocks, Bonds (and Options), Redux[†]

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Abstract

Are there risk factors that are pervasive across major classes of corporate securities: stocks, bonds, and options? We employ a novel econometric procedure that relies on asset characteristics to estimate a conditional latent factor model. A common risk factor structure prominently emerges across asset classes. Several common factors explain a substantial amount of time-series variation of individual asset returns across all three asset classes, and have sizable Sharpe ratios. Several of our factors are highly correlated with some of asset-class-specific factors as well as macroeconomic and financial variables. While a small set of common factors does not fully capture the cross-section of average returns, imposing the factor structure is useful in practice, especially in out-of-sample analysis. A mean-variance efficient portfolio that utilizes asset characteristics achieves a high Sharpe ratio as different asset classes hedge each other's exposures to the common factors.

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1 Introduction

Finance theory predicts a tight connection between the main types of corporate securities, such as stocks, corporate bonds, and options (Black and Scholes, 1973; Merton, 1974). A related pillar of asset pricing is that expected returns should reflect assets' loadings on pervasive common factors (Ross, 1976). Yet researchers have struggled to identify risk factors that are both common to all major asset classes and able to explain substantial variation in expected returns. Consequently, much of the asset pricing literature has pursued factors that are specific to a particular asset class.[1]

Empirical challenges have impeded efforts to extract common factors from individual assets across different markets. Many securities, such as options, have short time series. Additionally, asset classes such as corporate bonds and options contain far more securities than time observations, making traditional factor estimation unstable. The dimensionality and limited time spans have prevented the joint extraction of factors.

In this paper, we introduce a new econometric approach, the regressed-PCA method from Chen, Roussanov, and Wang (2023), to extract latent factors directly from individual securities. The key advantage of this new approach is that it works effectively with short time series and large cross-sections. The regressed-PCA method combines the familiar structure of Fama–MacBeth cross-sectional regressions (Fama and MacBeth, 1973) with principal component analysis (PCA) in a semi-parametric framework. More precisely, we model time-varying factor loadings and pricing errors as functions of observable characteristics, transforming a high-dimensional, unbalanced panel of assets into a smaller set of characteristic-managed portfolios. We then apply standard PCA to these portfolios to uncover the latent factors. Chen, Roussanov, and Wang (2023) show that the regressed-PCA estimators have desirable

[1] Fama and French (1993) explore common variation in stock and bond returns and find that stock returns are linked to bond returns through shared variation in the bond-market factors, but conclude that the key factors responsible for the risk premia are largely asset class-specific, which is the approach pursued by Coval and Shumway (2001) for option returns and Lustig, Roussanov, and Verdelhan (2011) for currency returns.

large-N asymptotic properties even when the time dimension is limited, making it well suited for studying joint factor structures across multiple asset classes.

Turning to the empirical implementation, we focus on the period during which comprehensive data for all three asset classes are available. Our sample consists of monthly observations from June 2004 to December 2021. The analysis incorporates 35 characteristics for stocks, 26 for corporate bonds, and 19 for options, spanning both firm-level and security-specific attributes.

Our key finding is the strong and systematic commonality across corporate asset classes. First, the extracted latent factors connect tightly to well-established observable pricing factors in stocks, corporate bonds, and options. Several latent factors load significantly on observable factors from all three markets. The leading latent factor, which explains the largest share of joint return variation, is significantly correlated with fifteen of the eighteen observable factors that we examine and closely aligns with their first principal component. Second, the characteristic loadings reveal that the latent factors draw meaningful information from all asset classes, rather than being dominated by any single market. Third, the latent factors have clear macro-financial interpretations. Many factors exhibit strong correlations with economic and financial uncertainties, intermediary capital factor, monetary and credit conditions, and real activities.

The latent common factor model delivers substantial explanatory and predictive power. In sample, ten regressed-PCA factors explain over 65 percent of the variation in characteristic-managed portfolios; out of sample, these factors capture over 28 percent of next-period returns. Notably, joint estimation outperforms asset-class-specific models, especially in options, where separate estimation often often yields negative out-of-sample fit. The factors also exhibit economically significant risk premia, with the leading factor achieving an annualized in-sample Sharpe ratio of 0.83.

Although corporate asset classes exhibit a common factor structure, the factors alone do not fully capture the cross-sectional returns. Using the regressed-PCA approach, we can explicitly separate the latent factors from the pricing errors orthogonal to them. The estimation of pricing errors allows us to construct a "pure-alpha" arbitrage portfolio that exploits the predictive power of characteristics while maintaining zero exposure to the latent common factors. The pure-alpha strategy generates a substantial out-of-sample Sharpe ratio over 2, significantly exceeding that of the factors. The out-of-sample Sharpe ratio does not decline when more factors are included, suggesting that the high average return on the pure-alpha strategy is not simply attributed to omitted factors. Moreover, we decompose the pure-alpha portfolio to examine the sources of pricing errors among asset classes. The results reveal that the strategy loads heavily on option-based characteristics, such as implied volatility and option gamma.

We further investigate the portfolio implications of the latent factors and pricing errors. Using the conditional covariance implied by the regressed-PCA model, we construct both in-sample and out-of-sample mean-variance efficient (MVE) portfolios jointly across stocks, corporate bonds, and options. The joint MVE portfolios deliver substantially higher Sharpe ratios than their asset-class-specific counterparts. In particular, we find that the MVE portfolios implicitly eliminate latent common factor exposures by exploiting heterogeneity in factor loadings across asset classes. The resulting optimal portfolio is effectively a "pure-alpha" strategy driven by mispricing rather than compensated factor exposure. Our findings suggest two key conclusions. First, the latent factors are important, as they successfully capture substantial common variation across markets. Second, however, the risk premiums associated with these factors are not comparable to the magnitude of the pricing errors. Thus, it is meaningful to hedge out latent factor exposures to exploit pure alphas.

Our paper contributes to a voluminous empirical asset pricing literature that studies the joint cross-section of multiple asset classes. Extensive research has documented predictive linkages between stocks and bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005b; Bali, Goyal, Huang, Jiang, and Wen, 2022; Dickerson, Julliard, and Mueller, 2024), stocks and options (Cao and Han, 2013; Bali, Beckmeyer, Moerke, and Weigert, 2021; Christoffersen, Goyenko, Jacobs, and Karoui, 2018; Bali and Hovakimian, 2009; Johnson and So, 2012; Xing, Zhang, and Zhao, 2010; Goyenko and Zhang, 2021), and bonds and options (Cao, Goyal, Xiao, and Zhan, 2022). Beyond these bilateral linkages, studies such as Asness, Moskowitz, and Pedersen (2013), He, Kelly, and Manela (2017), and Lettau, Maggiori, and Weber (2014) propose unified macro-finance factors that price assets jointly across various asset classes. However, robust evidence for common factor pricing remains elusive (Gospodinov and Robotti, 2021). Our study adds to this literature by estimating the latent factors that drive common variation while explicitly accounting for the pricing errors that arise from asset-specific dynamics.

Our paper also adds to the growing asset pricing literature in corporate bonds and options. These two asset classes are relatively under-studied compared to the equity class, though recent work has begun to map their specific factor structures. In corporate bonds, Kelly, Palhares, and Pruitt (2022) apply Instrumented Principal Component Analysis (IPCA) to identify five latent factors driving returns, while others emphasize specific risks like liquidity (Lin, Wang, and Wu, 2011), long-run consumption risk (Elkamhi, Jo, and Nozawa, 2022), or institutional constraints (Bali, Subrahmanyam, and Wen, 2021). In the options market, research has moved from parametric models (Duffie, Pan, and Singleton, 2000) to factor-based explanations. Büchner and Kelly (2022) use IPCA to explore the latent structure of index options, while Horenstein, Vasquez, and Xiao (2020) exploit asymptotic principal component analysis on option portfolios. Similarly, Christoffersen, Fournier, and Jacobs (2018) extract principal components from the implied volatility surface to explain the cross-section of option prices, and Karakaya (2013) suggests a three-factor model (level, slope, value) for delta-hedged returns. Others focus on specific characteristics such as embedded leverage (Frazzini and Pedersen, 2021; Goyal and Saretto, 2009; Zhan, Han, Cao, and Tong, 2022).

Our work is closely related to Bali, Beckmeyer, and Goyal (2023), who extend the IPCA approach to construct a joint factor model for corporate asset classes. They find that six latent factors are sufficient to explain a large proportion of total variations across these asset classes. While we agree that latent factors capture significant return variation, we find the factor structure fails to fully explain the cross-section of returns. Consistent with Daniel, Mota, Rottke, and Santos (2020), who show that characteristics often outperform factor loadings because the factors themselves contain unpriced risk, we demonstrate that substantial premia remain in the pricing errors, particularly in stocks and options. Consequently, we show that imposing the factor structure and hedging out the common factor exposures, while exploiting the characteristic-based pricing errors for expected returns, maximizes portfolio mean-variance efficiency.

The rest of the paper is organized as follows. Section 2 outlines the conditional factor model, introduces the regressed-PCA estimation procedure, and describes the evaluation metrics used in our empirical analysis. Section 3 introduces the data. Section 4 presents the main empirical results on the extracted common latent factors. Section 5 examines how the common risk factors relate to the cross-section of asset returns. Section 6 discusses the role of the common risk factors in the MVE portfolio allocation. Section 7 concludes.

2 Methodology

In this section, we introduce a general conditional factor model for individual assets' excess returns, which can identify factors within each asset class separately. We then extend the model to extract common factors jointly from returns on stocks, corporate bonds, and options. To estimate this conditional factor model, we apply the regressed-PCA methodology developed by Chen, Roussanov, and Wang (2023). Finally, we present several evaluation metrics to assess the in-sample fit and out-of-sample predictability of the estimated factor models.

2.1 Model

Following Chen, Roussanov, and Wang (2023) and Kelly, Pruitt, and Su (2019), we consider the following factor model, for $i = 1, ..., N$ and $t = 1, ..., T$,

$$r_{i,t} = \alpha(z_{i,t-1}) + \beta(z_{i,t-1})' f_t + \epsilon_{i,t}, \tag{2.1}$$

where $r_{i,t}$ is the monthly excess return of asset i at time t, and f_t is a $K \times 1$ vector of latent factors. Both the dynamic factor loadings $\beta(\cdot)$ and the mispricing errors $\alpha(\cdot)$ depend on $z_{i,t-1}$, which is a $(J+1) \times 1$ vector of observable time-varying characteristics for asset i at time $t-1$, and $\epsilon_{i,t}$ is the idiosyncratic error term.

Next, we specify the mispricing errors $\alpha(\cdot)$ and the dynamic factor loadings $\beta(\cdot)$. This paper focuses on linear approximations of the unknown functions $\alpha(z_{i,t-1})$ and $\beta(z_{i,t-1})$ in (2.1). Specifically, we assume they are approximated by

$$\alpha_{i,t} = a' z_{i,t} + \eta_{\alpha,i,t}, \quad \beta_{i,t} = B' z_{i,t} + \eta_{\beta,i,t}, \tag{2.2}$$

where $z_{i,t} = (1, z_{i,t,1}, \ldots, z_{i,t,J})'$, a is a $(J+1) \times 1$ vector, and B is a $(J+1) \times K$ matrix of loading coefficients. $\eta_\alpha(z_{i,t})$ and $\eta_\beta(z_{i,t})$ are the approximation errors.

Define $R_t \equiv (r_{1,t}, ..., r_{N,t})'$, $Z_{t-1} \equiv (z_{1,t-1}, ..., z_{N,t-1})'$, $\varepsilon_t \equiv (\epsilon_{1,t}, ..., \epsilon_{N,t})'$, $H_{\alpha,t-1} \equiv (\eta_{\alpha,1,t-1}, \ldots, \eta_{\alpha,N,t-1})'$ and $H_{\beta,t-1} \equiv (\eta_{\beta,1,t-1}, \ldots, \eta_{\beta,N,t-1})'$. Then rewriting (2.1) in matrix form gives

$$R_t = Z_{t-1} a + Z_{t-1} B f_t + H_{\alpha,t-1} + H_{\beta,t-1} f_t + \varepsilon_t. \tag{2.3}$$

Letting $\xi_t = H_{\alpha,t-1} + H_{\beta,t-1} f_t + \varepsilon_t$, we rewrite (2.3) into the following matrix form

$$R_t = Z_{t-1} a + Z_{t-1} B f_t + \xi_t. \tag{2.4}$$

Next, to capture the common factor structure across all three asset classes, we model that their returns load on a shared set of latent common factors (f_t^C). Then the returns on stocks (s), corporate bonds (b), and options (c) follow the factor models

$$\begin{aligned} R_t^s &= Z_{t-1}^s a_{C,s} + Z_{t-1}^s B_{C,s} f_t^C + \xi_t^s, \\ R_t^b &= Z_{t-1}^b a_{C,b} + Z_{t-1}^b B_{C,b} f_t^C + \xi_t^b, \\ R_t^o &= Z_{t-1}^o a_{C,o} + Z_{t-1}^o B_{C,o} f_t^C + \xi_t^o. \end{aligned} \tag{2.5}$$

Stacking these yields the compact matrix form:

$$\underbrace{\begin{bmatrix} R_t^s \\ R_t^b \\ R_t^o \end{bmatrix}}_{\mathbf{R}_t} = \underbrace{\begin{bmatrix} Z_{t-1}^s & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & Z_{t-1}^b & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & Z_{t-1}^o \end{bmatrix}}_{\mathbf{Z}_{t-1}} \underbrace{\begin{bmatrix} a_{C,s} \\ a_{C,b} \\ a_{C,o} \end{bmatrix}}_{\mathbf{a}} + \underbrace{\begin{bmatrix} Z_{t-1}^s & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & Z_{t-1}^b & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & Z_{t-1}^o \end{bmatrix}}_{\mathbf{Z}_{t-1}} \underbrace{\begin{bmatrix} B_{C,s} \\ B_{C,b} \\ B_{C,o} \end{bmatrix}}_{\mathbf{B}} f_t^C + \underbrace{\begin{bmatrix} \xi_t^s \\ \xi_t^b \\ \xi_t^o \end{bmatrix}}_{\boldsymbol{\xi}_t}. \tag{2.6}$$

This allows us to rewrite the common factor model compactly as:

$$\mathbf{R}_t = \mathbf{Z}_{t-1}\mathbf{a} + \mathbf{Z}_{t-1}\mathbf{B} f_t^C + \boldsymbol{\xi}_t. \tag{2.7}$$

In addition, we can apply the model in (2.4) to study the returns of each asset class separately. This allows us to analyze asset-class factors independently.

2.2 Regressed-PCA

We estimate the model in (2.4) and (2.7) following Chen, Roussanov, and Wang (2023) and apply the regressed-PCA approach. We use the model in (2.4) to illustrate the estimation procedure. The regressed–PCA approach proceeds in two steps.

Step 1: For each period t, run the cross-sectional regression of R_t on Z_{t-1} to obtain

$$\tilde{R}_t = a + Bf_t + (Z_{t-1}'Z_{t-1})^{-1}Z_{t-1}'\xi_t, \tag{2.8}$$

where $\tilde{R}_t = (Z_{t-1}'Z_{t-1})^{-1}Z_{t-1}'R_t$. This step is equivalent to a period-by-period Fama–MacBeth regression (Fama and MacBeth, 1973). The vector $\tilde{R}_t$ can be interpreted as the returns on

$J+1$ characteristic-managed portfolios, or as a set of cross-sectional factors in the sense of Fama and French (2020). See Chen, Roussanov, and Wang (2023) for further asset pricing interpretations.

Step 2: Apply standard PCA to the managed portfolios, $\{\tilde{R}_t\}_{1:T}$. Let $M_T \equiv I_T - 1_T 1_T'/T$ where 1_T denotes a $T \times 1$ vector of ones, $\tilde{R} \equiv (\tilde{R}_1, \dots, \tilde{R}_T)$, and $F \equiv (f_1, \dots, f_T)'$. We follow Chen, Roussanov, and Wang (2023) and impose the following identification restrictions: $a'B = 0$, $B'B = I_K$ and $F'M_T F/T$ being diagonal with descending entries. Then from PCA, we can get $\hat{B}$, the estimator of B, as the eigenvectors corresponding to the first K largest eigenvalues of the $(J+1) \times (J+1)$ matrix $\tilde{R} M_T \tilde{R}'/T$ and $\hat{a} = (I_{J+1} - \hat{B}\hat{B}') \sum_{t=1}^{T} \tilde{R}_t/T$. Note that B and f can be identified up to a rotation matrix. The corresponding estimators of $\alpha(\cdot)$, $\beta(\cdot)$ and f are

$$\hat{\alpha}(z) = \hat{a}'z, \hat{\beta}(z) = \hat{B}'z \text{ and } \hat{f} = (\hat{f}_1, \dots, \hat{f}_T)' = \tilde{R}'\hat{B}.$$

The model in (2.7) with common factors is estimated analogously. The first step consists of regressing $\mathbf{R}_{t+1}$ on $\mathbf{Z}_t$, which is equivalent to running separate cross-sectional regressions within each asset class. This yields characteristic-managed portfolios across asset classes. The second step is identical, we apply PCA to the pooled set of managed portfolios from all three asset classes.[2]

The advantage of applying regressed-PCA in our empirical setting is twofold. First, as shown in Section 3, we observe only 210 monthly periods but more than 1,000 individual assets for each asset class at every point in time, so the cross-sectional size is much larger than the time-series length ($N \gg T$). Regressed-PCA has large-N asymptotic properties that do not require T to be large (Chen, Roussanov, and Wang, 2023). Second, it accommodates unbalanced panels by transforming the unbalanced returns of individual assets into a bal-

[2]This procedure assumes a known number of factors K. In our empirical analysis, we examine a range of K values. Consistent estimates of K can also be obtained by maximizing the ratio of adjacent eigenvalues; see Ahn and Horenstein (2013) and Chen, Roussanov, and Wang (2023).

anced set of $J+1$ characteristic-managed portfolios through cross-sectional Fama–MacBeth regressions in each period. This property is crucial for options, where time-to-maturity is short, long-maturity contracts are illiquid, and thus balanced panels with many options over long horizons are infeasible.

For the out-of-sample estimation, we use an expanding window starting with 60 months of data. For each $t \geqslant 60$, we estimate the model using data through $t-1$ to obtain $\hat{a}_{t-1}$, $\hat{B}_{t-1}$, $\hat{f}^{(t-1)} \equiv (\hat{f}_1^{(t-1)}, \ldots, \hat{f}_{t-1}^{(t-1)})$, and the corresponding $\hat{\alpha}_{t-1}(z_{i,t-1}) = \hat{a}'_{t-1} z_{i,t-1}$, $\hat{\beta}_{t-1}(z_{i,t-1}) = \hat{B}'_{t-1} z_{i,t-1}$. We introduce the out-of-sample estimates of factors in Section 2.3.

2.3 Evaluation Metrics

In this section, we introduce several evaluation metrics to assess the in-sample and out-of-sample pricing performance of the factor models. We first consider three R^2s for in-sample fit. The first, R^2_K, is from the Fama–MacBeth cross-sectional regression in the second step (PCA) and measures how well the factors explain the characteristic-managed portfolios. The second, $R^2_{\tilde{R}}$, is from the first-step regression and measures how well the characteristic-managed portfolios explain individual assets. Finally, the total R^2 evaluates the model's ability to explain individual asset returns directly:

$$R^2 = 1 - \frac{\sum_{i,t} [r_{i,t} - \hat{\alpha}(z_{i,t-1}) - \hat{\beta}(z_{i,t-1})' \hat{f}_t]^2}{\sum_{i,t} r_{i,t}^2}. \tag{2.9}$$

Second, we compute three predictive R^2s: (i) the total out-of-sample R^2_O, (ii) $R^2_{T,N,O}$, the cross-sectional average of each asset's time-series predictability, and (iii) $R^2_{N,T,O}$, the time-series average of cross-sectional predictability, which reflects the model's ability to explain the cross-section of average returns (related to the Fama–MacBeth R^2). We approximate the time-t factor f_t by the average of all past factor estimates: $\hat{\lambda}_t = \sum_{s \leqslant t-1} \hat{f}_s^{(t-1)} / (t-1)$.

The formulas are:

$$R_O^2 = 1 - \frac{\sum_{i,t\geqslant 60}[r_{i,t} - \hat{\alpha}_{t-1}(z_{i,t-1}) - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{\lambda}_t]^2}{\sum_{i,t\geqslant 60} r_{i,t}^2}, \tag{2.10}$$

$$R_{T,N,O}^2 = 1 - \frac{1}{N}\sum_i \frac{\sum_{t\geqslant 60}[r_{i,t} - \hat{\alpha}_{t-1}(z_{i,t-1}) - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{\lambda}_t]^2}{\sum_{t\geqslant 60} r_{i,t}^2}, \tag{2.11}$$

$$R_{N,T,O}^2 = 1 - \frac{1}{T-60}\sum_{t\geqslant 60} \frac{\sum_i[r_{i,t} - \hat{\alpha}_{t-1}(z_{i,t-1}) - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{\lambda}_t]^2}{\sum_i r_{i,t}^2}. \tag{2.12}$$

Third, we assess out-of-sample fit. We define the out-of-sample realized factor returns at t as:

$$\hat{f}_{t-1,t} = \left[(Z_{t-1}\hat{B}_{t-1})'(Z_{t-1}\hat{B}_{t-1})\right]^{-1}(Z_{t-1}\hat{B}_{t-1})'(R_t - Z_{t-1}\hat{a}_{t-1}) \tag{2.13}$$

Then we plug them into the following three R^2's to evaluate how much the cross-sectional variation of individual assets can be explained by the factors,

$$R_{f,O}^2 = 1 - \frac{\sum_{i,t\geqslant 60}[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_{i,t\geqslant 60} r_{i,t}^2}, \tag{2.14}$$

$$R_{f,T,N,O}^2 = 1 - \frac{1}{N}\sum_i \frac{\sum_{t\geqslant 60}[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_{t\geqslant 60} r_{i,t}^2}, \tag{2.15}$$

$$R_{f,N,T,O}^2 = 1 - \frac{1}{T-60}\sum_{t\geqslant 60} \frac{\sum_i[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_i r_{i,t}^2}. \tag{2.16}$$

Fourth, we evaluate the out-of-sample performance using an arbitrage portfolio from a pure-alpha trading strategy based on the estimated anomaly terms $\hat{\alpha}(\cdot)$. In the unrestricted model, characteristics may capture mispricing reflected in the anomaly intercepts, independent of risk-based compensation. If the model accurately captures the risk-return relation, this strategy should yield a high Sharpe ratio. The portfolio weights are

$$w_t^\alpha = Z_{t-1}\left(Z_{t-1}'Z_{t-1}\right)^{-1}\hat{a}_{t-1}. \tag{2.17}$$

Chen, Roussanov, and Wang (2023) show that the return on this portfolio converge to $\|a\|^2$.

Finally, we employ the weighted bootstrap procedure from Chen, Roussanov, and Wang (2023) to test the hypotheses $a = 0$ and $B = 0$.

3 Data

This section introduces the data for stocks, corporate bonds, and options. We present key filters for corporate bonds and options, along with summary statistics for returns. We also briefly describe the characteristics that compose the latent factor loadings and mispricing errors in our return model across the three asset classes. Appendix A1 provides detailed descriptions of the characteristics and filters used in our analyses.

To extract joint factors, we focus on the sample period during which data for all three asset classes are available. Thus, our in-sample analysis covers July 2004 to December 2021 for monthly stock, bond, and option returns. For out-of-sample analysis, the sample runs from July 2004 to December 2019, with the first 60 months as the initial training period. We exclude the subsequent two years, which include extraordinary events such as COVID-19 and the GameStop episode, as these events substantially affect out-of-sample predictability, especially for equity options. As a robustness check, we extend the sample to December 2021 for out-of-sample analyses, and report the results in Appendix A5.

For all asset classes, we study excess returns, using risk-free rates from Kenneth French's data library.[3] We rescale all characteristics cross-sectionally to the range $[-0.5, +0.5]$ to limit the influence of outliers, following Kelly, Pruitt, and Su (2019).

3.1 Stocks

The stock returns and characteristics data are originally from Freyberger, Neuhierl, and Weber (2020) and Kim, Korajczyk, and Neuhierl (2021). To model stock returns, we pick 35 characteristics that are available from Freyberger, Höppner, Neuhierl, and Weber (2022),

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

out of 36 characteristics which are used in Kelly, Pruitt, and Su (2019) and Chen, Roussanov, and Wang (2023).[4] The 35 characteristics are market beta (*beta*), market capitalization (*mktcap*), book-to-market ratio (*bm*), gross profitability (*prof*), investment (*invest*), idiosyncratic volatility (*idiovol*), book leverage (*lev*), operating leverage (*ol*), momentum (*mom*), intermediate momentum (*intmom*), short-term reversal (*strev*), long-term reversal (*ltrev*), average daily bid-ask spread (*bidask*), standard unexplained volume (*suv*), price to 52-week high price (*w52h*), total assets (*asset*), total-assets-to-size (*a2me*), sales-to-lagged-net-operating-assets (*ato*), sales-to-price (*s2p*), cash-to-short-term-investment (*c*), capital turnover (*cto*), ratio of change in property, plants and equipment to the change in total assets (*dpi2a*), earnings-to-price (*e2p*), return on net operating assets (*rna*), return on assets (*roa*), return on equity (*roe*), price-to-cost margin (*pcm*), profit margin (*pm*), Tobin's Q (*q*), cash flow-to-book (*freecf*), last month's volume to shares outstanding (*turn*), capital intensity (*d2a*), operating accruals (*oa*), ratio of sales and general administrative costs to sales (*sga2s*), and net operating assets (*noa*). For detailed definitions and summary statistics of these characteristics, see Freyberger, Neuhierl, and Weber (2020) and Freyberger, Höppner, Neuhierl, and Weber (2022).

3.2 Corporate Bonds

For corporate bonds, we use the dataset constructed by Dickerson, Robotti, and Rossetti (2023).[5] This corporate dataset sources from the WRDS bond database and Mergent's FISD. A highlight in this dataset is that the corporate bond prices are properly adjusted for market microstructure noises (MMN) in the trades by following the procedure proposed

[4] Kelly, Pruitt, and Su (2019) and Chen, Roussanov, and Wang (2023) choose 36 stock characteristics from Freyberger, Neuhierl, and Weber (2020), but the sample ends in May 2014. Freyberger, Höppner, Neuhierl, and Weber (2022) extend the characteristics data in Freyberger, Neuhierl, and Weber (2020) to December 2021 and impute the missing values in a GMM framework. The extended dataset is generously provided by the authors. The only characteristic that is absent from this new dataset is fixed costs-to-sales (*fc2y*).

[5] We are sincerely grateful that the authors kindly provide the dataset to us.

by Andreani, Palhares, and Richardson (2023), so that the asset pricing implications can be closely aligned with the industry-grade quote data such as ICE.

The dataset from Dickerson, Robotti, and Rossetti (2023) include monthly variables of corporate bond returns, as well as bond-level characteristics. We complement their dataset with Mergent's FISD to construct additional bond characteristics. The Mergent's FISD dataset has basic issue information such as bond interest rates, convertible terms, bondholder protections, and unit offerings. It also provides issuer information as well as corresponding agencies. We merge the dataset from Dickerson, Robotti, and Rossetti (2023) with Mergent's FISD based on bond security's CUSIP. The bond returns and characteristics are then merged with firm-level characteristics using the WRDS Bond CRSP Link table.

The monthly corporate bond returns are computed using representative price (P) for each end-of-month date and each bond, accrued interests (AI), and coupons (cpn). First, since corporate bond markets are illiquid, and trades may or may not occur frequently within the month, the end-of-month prices should balance the trade-offs between keeping a large enough sample size and extrapolating from the last available prices. Specifically, for each corporate bond on each month-end date, we select the price if it is available within 5 calendar days before the month-end; otherwise, we mark the price as missing.[6] Second, we compute the accrued interest over the fractional period between the last coupon payment date and the month-end date. We can compute the monthly return as:

$$R_{t+1}^{corpbond} = \frac{P_{t+1} + AI_{t+1} + cpn_{t+1}}{P_t + AI_t} - 1.$$

We employ 26 characteristics that are widely studied by the literature on corporate bond returns (e.g., Kelly, Palhares, and Pruitt, 2022; Bao, Pan, and Wang, 2011) in our model. There are 12 bond contract level characteristics, including bond age (age), coupon (cpn),

[6] In the WRDS bond database, the variable name is RET_L5M.

rating (*rating*), issue amount (*issue_size*) duration (*duration*), spread (CS), bond momentum (*bond_mom*), spread momentum (*spread_mom*), value-at-risk (VaR), bond short-term reversal (*bond_rev*), bond long-term reversal (*bond_ltrev*), and illiquidity (*illiq*). We also include 14 stock-level variables, which are idiosyncratic volatility (*idiovol*), momentum (*mom*), book leverage (*lev*), Fama-French five-factor related characteristics (*beta*, $prof$, *mktcap*, *invest*, *bm*), operating leverage (*ol*), earnings-to-price ratio (*e2p*), tangibility (*tan*), total debt (*debt*), debt-to-EBITDA (*d2ebitda*), and distance-to-default (DD). Appendix A1 presents the sources and detailed description of these characteristics.

3.3 Options

We obtain individual equity options data is from OptionMetrics, and underlying stock information such as stock returns, prices, share code, and trading volume from CRSP.

To avoid recording errors and exclude extremely illiquid options, we apply standard filters used in the literature.[7] All filters rely only on information available at the portfolio formation date t to avoid look-ahead bias. Appendix A1 provides full details.

Outliers in the options data can significantly distort the estimation of factors, especially during periods of extreme market activity (e.g., the GME episode). To mitigate this, we trim the options data by excluding returns below the 1st percentile and above the 99th percentile in each period. The trimmed sample is used only for in-sample estimation. Because this trimming introduces potential look-ahead bias, we do not use trimmed data in out-of-sample analysis.[8]

We focus on call options as calls are more actively traded (Zhan, Han, Cao, and Tong, 2022; Christoffersen, Goyenko, Jacobs, and Karoui, 2018). Then we compute delta-hedged

[7] See Büchner and Kelly (2022), Frazzini and Pedersen (2021), Zhan, Han, Cao, and Tong (2022), Bali, Beckmeyer, Moerke, and Weigert (2021), Goyenko and Zhang (2021), Goyal and Saretto (2009), and Boyer and Vorkink (2014).

[8] We report out-of-sample results using trimmed data in Appendix A5.

holding returns. At the portfolio formation date, we buy one call option contract and sell Δ shares of the underlying stock, where Δ is from OptionMetrics and calculated under the Black–Scholes model. We hold the position for one month without daily rebalancing to reduce transaction costs and improve practicality. Then the delta-hedged return is defined as

$$R_{t+1}^{option} = 1 - \frac{\Delta_t S_{t+1} - C_{t+1}}{\Delta_t S_t - C_t}.$$

Our return model includes 19 characteristics documented in the literature as useful for describing and predicting option returns (e.g., Büchner and Kelly, 2022; Zhan, Han, Cao, and Tong, 2022; Bali, Beckmeyer, Moerke, and Weigert, 2021). Seven are contract-level: implied volatility (*impl_vol*), the option's Greeks (*delta*, *gamma*, *theta*, *volga*), embedded leverage (*embed_lev*), and an option illiquidity measure (*optspread*). Twelve are stock-level: stock illiquidity (*bidask*), idiosyncratic volatility (*idiovol*), volatility deviation (*vol_dev*), momentum measures (*strev*, *intmom*, *mom*), book leverage (*lev*), and Fama–French five-factor–related characteristics (*beta*, *prof*, *mktcap*, *invest*, *bm*). Appendix A1 provides detailed definitions and references for each characteristic.

3.4 Summary Statistics and Standardization

Table 1 reports descriptive statistics for returns on the three asset classes; for options, we use the trimmed returns described above. After filtering, we retain 738,518 stock–month observations, 208,652 corporate bond–month observations, and 760,836 option–month observations. Each period contains at least 386 observations for each asset class, enabling a comprehensive analysis of the common factor structure across individual assets.

Table 1 shows large differences in return standard deviations across asset classes. As is standard in PCA, we scale returns to account for these volatility differences by dividing all returns in each asset class by the standard deviation of all returns in that class. This step prevents high-volatility assets from dominating the principal components due to scale rather than stronger common factors. To avoid look-ahead bias, we compute these standard deviations using the first 60 periods, consistent with the initial window in the out-of-sample analysis.

4 Common Factors

Estimating the conditional factor model in (2.7) using the regressed-PCA approach yields a set of factors that capture common variation across stocks, corporate bonds, and options.[9] Figure 1 plots the cumulative returns of the first five regressed-PCA factors. Several factors exhibit strong systematic variation with major market episodes, indicating that these factors capture common sources of risk. In this section, we investigate the economic nature of the latent common factors along two dimensions: (i) their relation to different asset classes, and (ii) their relation to macroeconomic and financial variables.

4.1 Relation to Asset Classes

We begin by examining how the latent common factors are linked to different asset classes. First, we analyze their relation to observable factors from the literature that are specific to each asset class, and to the principal components of these observable factors. Second, we investigate how the common factors relate to regressed-PCA factors estimated separately within each asset class. Third, we study the contribution of asset characteristics to the beta loadings of the common factors. Finally, we decompose the common factors into asset-class constituents and evaluate their relative contributions.

[9] Unless otherwise noted, we focus on the unrestricted model ($\alpha(\cdot) \neq 0$). As shown in the next section, specification tests indicate that $\alpha(\cdot)$ is significantly non-zero.

4.1.1 Common Factors and Observable Factors

First, we examine the connection between the latent common factors and observable factors from the literature, each designed to explain return variation within a specific asset class. For stocks, we follow Fama and French (2015) and Carhart (1997) and include the market factor ($MKTstock$), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (MOM). For corporate bonds, we follow Bai, Bali, and Wen (2019) and Dickerson, Mueller, and Robotti (2023), selecting the bond market factor ($MKTbond$), credit risk (CRF), liquidity risk (LRF), bond momentum ($MOMB$), bond return reversal (REV^*), and long-term reversal (LTR). For options, we use factors from Goyal and Saretto (2009), Zhan, Han, Cao, and Tong (2022), and Büchner and Kelly (2022): volatility level ($LEVEL$), moneyness skewness ($SKEW$), idiosyncratic volatility ($IVOL$), illiquidity (ILQ), the option-market factor ($MKToption$), and volatility deviation ($VOLDEV$). Additional details on these observable factors are provided in Appendix A2.

Table 2 reports the correlations between the latent common factors and the observable factors. The latent common factors display strong correlations with a broad set of observable factors. Several of these factors are significantly related to multiple observable factors across asset classes. For example, the first common factor is highly correlated with fifteen out of eighteen observable factors, showing positive correlations with the stock, corporate bond, and option market factors. These findings suggest that the latent factors capture the common variation across asset classes.

Table 3 presents the time-series regression results of each latent common factor on observable factors. Several of the latent common factors are significantly explained by observable factors across asset classes. For example, the first common factor loads positively on SMB and RMW, and negatively on the stock MOM factor, consistent with the findings of Asness, Moskowitz, and Pedersen (2013) and Fama and French (2015);[10] it also loads significantly

[10] Asness, Moskowitz, and Pedersen (2013) document that value and momentum are pervasive across

on the credit risk and liquidity risk factors of Dickerson, Mueller, and Robotti (2023). Overall, observable pricing factors from the three asset classes account for a substantial share of the variation in the latent common factors, with adjusted R^2 values ranging from 19% to 57%. Nonetheless, almost all of the common factors continue to earn positive and significant returns beyond the observable factors, as reflected in positive intercepts in the regressions. The result suggests that these latent factors embed additional premiums that are not fully spanned by existing observable factors in the literature.

4.1.2 Common Factors and Principal Components of Observable Factors

We also examine how the latent common factors relate to the principal components of the observable factors. We first apply the standard PCA to the eighteen observable pricing factors. If asset classes exhibit common sources of variation, the corresponding observable factors are expected to load on a shared component structure.

As reported in Appendix A2, the first ten principal components collectively explain 88% of the variation, highlighting a strong common structure for observable pricing factors. In particular, the first principal component loads consistently across all three asset classes, explaining 20.5% of the variation in stock factors, 31.7% in corporate bond factors, and 44.9% in option factors.

Next, we assess how the latent common factors align with the component structure of the observable factors. The top panel of Figure 2 reports the correlations between the two sets of factors. The first regressed-PCA factor (Common 1) is strongly correlated (above 0.6) with the first principal component of the observable factors (PC 1), suggesting that the two approaches converge to identify a similar source of common variation across asset classes.

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financial markets and asset classes, including stocks, commodities, currencies, and government bonds. They also find that value and momentum are negatively correlated both within and across asset classes. Fama and French (2015) show that the role of the value factor is largely absorbed once profitability and investment factors are included.

The bottom panel plots the time series of Common 1 against PC 1. Both series track each other closely, particularly during major market episodes such as the global financial crisis of 2008–09 and the COVID-19 shock in 2020, when both drop sharply. The overall pattern suggests that the latent common factors and the principal components of observable factors capture a systematic dynamic shared across asset classes.

4.1.3 Common Factors and Asset-Class-Specific Latent Factors

We compare the latent common factors with the latent factors estimated separately from each asset class using the reduced model in (2.4). Table 4 reports the correlations between the two sets of factors. The leading latent common factor (Common 1) loads strongly on all three asset markets: it is highly correlated with the first stock latent factor (0.85), and also shows significant correlations with the first three corporate bond factors (0.62, 0.32, 0.24) and the first two option factors (0.44 and 0.14).

Other latent common factors also show relations across asset classes. For example, the second common factor is strongly related to the first option factor (0.80) and negatively associated with the first corporate bond factor (–0.53), while showing little connection to stock-specific factors. This pattern suggests that it reflects risks jointly priced in options and corporate bonds. The third common factor likewise exhibits significant correlations with various class-specific factors from all three asset markets.

Overall, these findings indicate that the latent common factors are not tied to a single asset market, but instead capture common sources of variation across asset classes.

4.1.4 Characteristics Loadings and Asset-Class Constituents

The regressed-PCA approach provides a direct way to examine how asset-level characteristics contribute to the construction of the common factors, specifically through the beta loadings.

Analyzing this anatomy sheds light on the systematic risk sources underlying the factors.

For illustration, Figure 3 plots the estimated coefficients B on the first latent common factor across all characteristics. The figure shows that the first factor has significant beta loadings from characteristics across stocks, corporate bonds, and options. The cross-asset-class loadings provide evidence that the regressed-PCA factors capture common components of variation across markets. Further discussion of the characteristic loadings is provided in Appendix A3.

While characteristics highlight the micro-level anatomy of factor construction, it is also important to examine how entire asset classes contribute to these common factors. An appealing feature of the regressed-PCA approach is that each factor can be expressed as the sum of its asset-class constituents:

$$\hat{f}^C = \tilde{\mathbf{R}}'\hat{\mathbf{B}} = \tilde{\mathbf{R}}_{\mathrm{S}}'\hat{\mathbf{B}}_{\mathrm{S}} + \tilde{\mathbf{R}}_{\mathrm{B}}'\hat{\mathbf{B}}_{\mathrm{B}} + \tilde{\mathbf{R}}_{\mathrm{O}}'\hat{\mathbf{B}}_{\mathrm{O}},$$

where $\tilde{\mathbf{R}}$ denotes the vector of characteristic-managed portfolio returns associated with all three asset classes, and $\hat{\mathbf{B}}$ is the estimated vector of beta loadings. The subscripts index the asset-class-specific elements of these vectors ($A \in \{\mathrm{Stock}, \mathrm{CorpBond}, \mathrm{Option}\}$). We therefore define each asset-class constituent as

$$\hat{f}_A = \tilde{\mathbf{R}}_A'\hat{\mathbf{B}}_A, \tag{4.1}$$

so that the common factors decompose as $\hat{f}^C = \hat{f}_{\mathrm{Stock}} + \hat{f}_{\mathrm{CorpBond}} + \hat{f}_{\mathrm{Option}}$.

Table 5 summarizes how each asset class contributes to the latent common factors by reporting their correlations and variance decompositions.[11] These results highlight that the latent factors effectively capture cross-asset commonality. All correlations are positive and significant, indicating that each asset-class constituent contributes meaningfully to the common factors. The first common factor (Common1) has high correlations of 0.89 for stocks,

[11] The variance decomposition is defined as the share of the common factor's total variance that can be attributed to each constituent, i.e., $\frac{\mathrm{Cov}(\hat{f}_A, \hat{f}^C)}{\mathrm{Var}(\hat{f}^C)}$.

0.74 for corporate bonds, and 0.51 for options. Its variance decomposition shows that stocks explain 57% of the factor's variation, followed by corporate bonds (29%) and options (14%). This pattern suggests that while stock constituent is the dominant contributor, corporate bond and option markets also play substantial roles in shaping the factor's behavior. Overall, all latent common factors load on multiple asset classes, reflecting the presence of common sources of variations.

4.2 Relation to Macroeconomic and Financial Variables

To better interpret the economic meaning of the latent common factors, we explore their relationships with a broad set of macroeconomic and financial variables. We group these variables into three categories: (i) indicators of economic activities, including core inflation, consumption growth, and growth in industrial production, (ii) uncertainty measures, including economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2016), financial uncertainty (FINU) and macro uncertainty (MACU) from Jurado, Ludvigson, and Ng (2015), (iii) financial conditions, including federal funds rate, term spread, credit spread, VIX index, intermediary capital factor (HKM) from He, Kelly, and Manela (2017), and the liquidity factor from Pástor and Stambaugh (2003). Several of these series are first-differenced, denoted $\Delta(\cdot)$, to ensure stationarity.

We explore the macro linkage from two perspectives. First, we examine the contemporaneous relations between the common factors and macro-financial variables, and analyze how asset-class constituents of the common factors contribute to these relations. Second, we evaluate the ability of the common factors to forecast and nowcast key macro-financial variables.

4.2.1 Common Factors and Macro-Financial Variables

Table 6 reports the pairwise correlations between the latent common factors and macro-financial variables. Several factors exhibit significant correlations with macroeconomic and financial series, indicating their relevance to underlying economic conditions. The first common factor is strongly linked to economic uncertainty and intermediary conditions: it is negatively correlated with uncertainty indexes and the VIX, and positively correlated with the intermediary capital factor (HKM). The second factor is negatively related to the federal funds rate and the credit spread, highlighting its connection to monetary and credit conditions. The third common factor shows strong positive associations with core inflation, consumption growth, and industrial production growth, suggesting that the factor reflects macroeconomic fundamentals.

Table 7 summarizes the regression results of the latent common factors on macro-financial variables. For the first factor, HKM provides the largest explanatory share, accounting for 29% of the Shapley–Owen R^2 decomposition,[12] followed by financial uncertainty (17%) and the term spread (10%). For the third factor, consumption and industrial production growth each explain more than 20% of the variance. More broadly, factors that capture larger cross-asset variation also exhibit stronger links to macro-financial variables: 38.6% and 32.4% of the variance in the first and third common factors can be explained, compared with less than 10% for factors seven through ten.[13]

The common factor decomposition in 4.1 allows us to identify which asset classes drive the links between common factors and macro-financial variables. For illustration, we regress

[12] The Shapley–Owen R^2 decomposition attributes explained variance to regressors by averaging their marginal contributions across all possible orderings of variables; see Huettner and Sunder (2012); Fournier, Jacobs, and Orłowski (2023).

[13] We also relate the latent common factors to the set of macroeconomic factors from Ludvigson and Ng (2009). The first common factor is correlated with their real economic activity, interest rate, and inflation factors, while the second common factor is significantly related to their stock market factor. The findings further support the interpretation that the latent common factors capture broad macroeconomic forces. Further details are provided in Appendix A4.

asset-class constituents of the first common factor on the macro-financial variables. The results are reported in Table 8. The stock constituent is most strongly related to financial uncertainty and industrial production growth, and HKM. The corporate bond constituent loads on a broader set of variables, including term premia, credit spreads, macro uncertainty, and HKM. The option constituent is primarily driven by consumption growth, the federal funds rate, the VIX, and financial uncertainty. The results suggest that each asset class contributes distinct macro-financial exposures, with bonds most tightly connected to macro and credit risks, options linked to volatility and uncertainty, and stocks reflecting both real activity and intermediary constraints.

4.2.2 Forecasting and Nowcasting Macro-Financial Variables

To further examine the economic relevance of the latent common factors, we evaluate their ability to forecast and nowcast key macro-financial variables.

We begin by testing the forecasting ability. At each period t, we estimate the time-series regression of the following form:

$$Y_t = a^Y + \sum_{k=1}^{10} \gamma_{t-1}^{Y,k} f_{t-1}^{k,C} + \varepsilon_t^Y, \tag{4.2}$$

where Y_t is the macro-financial variable of interest, and f_{t-1}^k is the k-th latent common factor at $t-1$. From this regression we estimate $\{\hat{a}^Y, \hat{\gamma}_{t-1}^{Y,k}\}$.[14] Using these coefficients and the realized factors $\hat{f}_{t-1,t}^k$ at t,[15] we construct the one-step-ahead forecast of Y:

$$\tilde{Y}_t \equiv E_t[Y_{t+1}|f_t^k] = \hat{a}^Y + \sum_{k=1}^{10} \hat{\gamma}_{t-1}^{Y,k} \hat{f}_{t-1,t}^k. \tag{4.3}$$

We then test the predictive power of the common factors with the following regression:

$$Y_{t+1} = m + \xi \tilde{Y}_t + e_{t+1}. \tag{4.4}$$

[14] In estimating the coefficients at each period, we winsorize Y_t at the 1% and 99% levels to ensure stability, particularly during episodes such as COVID-19 when macro series display extreme values. In the prediction stage, Y_{t+1} is not winsorized. For nowcasting, Y_{t-1} is winsorized while Y_t is not.

[15] We use the out-of-sample realized factor returns $\hat{f}_{t-1,t}$ from (2.13).

For nowcasting, the procedure is similar but the timing differs. We estimate the weights using data up to $t-1$, and then use contemporaneous factor realizations to predict Y_t:

$$Y_{t-1} = a^{Y,now} + \sum_{k=1}^{10} \gamma_{t-1}^{Y,k,now} f_{t-1}^{k,C} + \varepsilon_{t-1}^{Y,now}, \tag{4.5}$$

$$\tilde{Y}_t^{now} \equiv \hat{a}^{Y,now} + \sum_{k=1}^{10} \hat{\gamma}_{t-1}^{Y,k,now} \hat{f}_{t-1,t}^{k}, \tag{4.6}$$

$$Y_t = m^{now} + \xi^{now} \tilde{Y}_t^{now} + e_t^{now}. \tag{4.7}$$

Table 9 reports the regression results. Panel A shows that the common factors have significant forecasting power for macroeconomic variables, especially core inflation, consumption growth, and industrial production growth. Panel B shows that the factors are most effective in nowcasting financial variables such as HKM, $\Delta(VIX)$, and $\Delta(FINU)$. Overall, the results suggest that the common factors contain both forward-looking information about macroeconomic activity and contemporaneous information about financial conditions.

5 Pricing the Joint Cross-Section of Returns

In this section, we evaluate the performance of the regressed-PCA common factors in pricing the joint cross-section of returns. Specifically, we examine the factor model's in-sample fit and out-of-sample predictability, assess the Sharpe ratios of the factors, and analyze the significance of pure-alpha strategies, i.e., portfolios with zero loadings on the common factors.

5.1 Performance of the Common Factor Model

We evaluate the in-sample and out-of-sample performance of the common factor model in (2.7), using the metrics introduced in Section 2.3.

Table 10 summarizes the results, showing that the common factor model provides strong explanatory and predictive power for the joint cross-section of returns. First, the common factors explain a large share of the in-sample variation in characteristic-managed portfolios across asset classes: with ten factors, the R_K^2 values exceed 65%. Second, the ten-factor model delivers an in-sample fit of 16.35% for the joint cross-section of individual asset returns, 11.51% for stocks, 33.99% for corporate bonds, and 19.53% for options. Third, the model also exhibits strong out-of-sample predictability: the realized common factors explain 27.95% of the variation in the joint cross-section of next-period returns, as measured by $R_{f,O}^2$. Notably, the first common factor alone accounts for most of the explained variation, with an out-of-sample fit of 25.96%.

Moreover, the common factor model often delivers stronger out-of-sample predictive power than the asset-class-specific latent factor model in (2.4), even though the latter is estimated separately for each market. For instance, Table A7 shows that the out-of-sample $R_{f,O}^2$ values for options under the option-specific model are frequently negative, largely due to outliers in option returns. By contrast, the common factor model has positive predictive power, as reported in Table 10. The comparison highlights that joint estimation uncovers common variation overlooked by asset-class-specific models, improving return predictability.

We also consider an alternative definition of out-of-sample realized factor returns,

$$\hat{f}^A_{t-1,t} = \hat{B}'_{t-1}(Z'_{t-1}Z_{t-1})^{-1}Z'_{t-1}R_t = \hat{B}'_{t-1}\tilde{R}_t. \tag{5.1}$$

Different from $\hat{f}_{t-1,t}$ in (2.13), $\hat{f}^A_{t-1,t}$ does not abstract from the pricing error term $\hat{\alpha}$. Table A6 reports the out-of-sample fit of $\hat{f}^A$. Compared with Table 10, the alternative factors show weaker out-of-sample fit for the joint cross section, suggesting that removing pricing errors from the factors improves their ability to capture the common variation in returns.

5.2 Risk Premia and Pricing Errors of the Common Factors

Do the regressed-PCA common factors carry significant risk premia? To address this question, we compute in-sample and out-of-sample Sharpe ratios of the regressed-PCA factors.

Table 11 reports the results. The regressed-PCA factors exhibit economically large in-sample premia. For example, the first regressed-PCA common factor achieves an annualized in-sample Sharpe ratio of 0.83. Out of sample, the Sharpe ratio of the first factor is 0.18 when realizations are defined using $\hat{f}_{t-1,t}$ in (2.13), which removes the pricing error term $\hat{\alpha}$. In comparison, when we use the alternative definition $\hat{f}^{A}_{t-1,t}$ in (5.1), the out-of-sample Sharpe ratio rises to 0.49. The comparison suggests that the out-of-sample premium for the first factor is largely attributable to the pricing error component.

Despite the sizable premia and strong fit, the regressed-PCA common factors do not fully span the cross-section of asset returns. To investigate the pricing error components, we evaluate the performance of the pure-alpha strategies, i.e., portfolios with zero loadings on the common factors that isolate residual pricing errors.

Table 12 reports the annualized means, standard deviations, and Sharpe ratios of the pure-alpha strategies. A portfolio constructed to have zero loading on the first regressed-PCA common factor delivers a high out-of-sample Sharpe ratio of 2.14. Expanding the set of factors does not eliminate this effect: even after controlling for all ten common factors, the pure-alpha portfolio continues to achieve a Sharpe ratio close to 2. The table further shows that average returns on pure-alpha portfolios decline as more factors are included, but portfolio volatility falls by an even greater margin, which drives a U-shaped pattern in Sharpe ratios. The decline in volatility indicates that the common factors effectively capture substantial shared variation across stocks, corporate bonds, and options. Nevertheless, the consistently high Sharpe ratios of the pure-alpha strategies reveal that a sizeable portion of the cross-sectional returns remains unexplained by the common factors.

We next turn to a formal model specification test of pricing errors. We test the null hypothesis $\alpha(\cdot) = 0$ using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023). Figure 4 reports the coefficient estimates and their 95% confidence intervals with ten factors included. Despite controlling for many common factors, several characteristics still load significantly in $\alpha(\cdot)$, generating nontrivial pricing errors. The test also helps identify the sources of the pure-alpha strategy's performance. Stock characteristics contribute modestly to the pure-alpha portfolio returns, consistent with the mature and liquid nature of equity markets where anomalies are quickly arbitraged away. Corporate bond characteristics also play a limited role, in line with recent evidence (e.g., Dickerson, Robotti, and Rossetti, 2023) showing that many bond return anomalies diminish once microstructure noises are addressed. In contrast, most of the option characteristics make significant contributions. The findings suggest that persistent anomalies in the option market help explain the strong performance of the pure-alpha strategy.

6 MVE Portfolios Across Asset Classes

In this section, we construct both in-sample and out-of-sample conditional mean-variance efficient (MVE) portfolios from individual securities jointly across asset classes. To address dimensionality and estimation noise, we employ characteristic-managed portfolios and impose a common factor structure that makes the MVE problem tractable. We evaluate the performance of the resulting portfolios, and discuss their hedging properties. In particular, we examine the extent to which the MVE portfolios hedge against common factors, and analyze the sources of hedging.

6.1 MVE Portfolio Construction

The conditional MVE portfolio choice problem at time t is defined as

$$\max_{\mathbf{w}_t} \left\{ \mathbf{w}_t' E_t \left[\mathbf{R}_{t+1}\right] - \frac{1}{2} \mathbf{w}_t' \operatorname{Var}_t \left[\mathbf{R}_{t+1}\right] \mathbf{w}_t \right\}, \tag{6.1}$$

where $\mathbf{w}_t$ denotes the portfolio weights, and $\mathbf{R}_{t+1}$ the individual excess returns. The solution for the optimal weights is $\mathbf{w}_t = \operatorname{Var}_t \left[\mathbf{R}_{t+1}\right]^{-1} E_t \left[\mathbf{R}_{t+1}\right]$.

However, applying the MVE portfolio choice directly to individual assets is challenging, because it requires estimating a high-dimensional sample covariance matrix. With thousands of assets but relatively limited time series, the estimation of covariance becomes unstable. In addition, many securities suffer from unbalanced panels and limited trading histories, with the problem most pronounced for options due to their short maturities.[16]

We address this challenge by employing characteristic-managed portfolios. Assuming that the idiosyncratic variance unexplained by characteristics is homoskedastic and uncorrelated across individual assets, the portfolio choice problem in (6.1) can be expressed as

$$\max_{\mathbf{w}_t} \left\{ \mathbf{w}_t' \mathbf{Z}_t E_t[\tilde{\mathbf{R}}_{t+1}] - \frac{1}{2} \mathbf{w}_t' \mathbf{Z}_t \operatorname{Var}_t[\tilde{\mathbf{R}}_{t+1}] \mathbf{Z}_t' \mathbf{w}_t - \frac{\sigma_t^2}{2} \mathbf{w}_t' \mathbf{w}_t \right\}, \tag{6.2}$$

with $\tilde{\mathbf{R}}_{t+1} = (\mathbf{Z}_t'\mathbf{Z}_t)^{-1}\mathbf{Z}_t'\mathbf{R}_{t+1}$. The solution for the optimal weights is

$$\mathbf{w}_t = \mathbf{Z}_t(\mathbf{Z}_t'\mathbf{Z}_t)^{-1} \left[\operatorname{Var}_t[\tilde{\mathbf{R}}_{t+1}] + \sigma_t^2 (\mathbf{Z}_t'\mathbf{Z}_t)^{-1} \right]^{-1} E_t[\tilde{\mathbf{R}}_{t+1}], \tag{6.3}$$

This reformulation translates the optimal portfolio choice problem over individual assets into a much simpler problem over a small set of characteristic-managed portfolios. Instead of estimating the mean and covariance of individual asset returns, we estimate the moments from managed portfolio returns $\tilde{\mathbf{R}}_{t+1}$.

To further mitigate estimation noise, we impose a common factor structure when esti-

[16] Alternative approaches based on large-dimensional covariance estimators (e.g., Ledoit and Wolf, 2017) are less suited to settings with unbalanced panels across asset classes. Our method complements this line of work by directly incorporating firm characteristics into portfolio construction, thereby providing conditional information that improves the approximation of MVE portfolios.

mating the covariance of returns. Under the common factor model in (2.7), the covariance matrix of characteristic-managed portfolios can be approximated as

$$\mathrm{Var}_t[\tilde{\mathbf{R}}_{t+1}] = B\,\mathrm{Var}_t\left[f_{t+1}\right]B', \tag{6.4}$$

where f_{t+1} denotes the common factors, and B the associated loadings. By doing so, we are able to consistently estimate the MVE portfolios both in-sample and out-of-sample. The conditional idiosyncratic variance is estimated in-sample as $\hat{\sigma}_t^2 = \frac{1}{N_t-1}\sum_{i=1}^{N_t}(R_{i,t+1} - Z'_{i,t}\tilde{\mathbf{R}}_{t+1})^2$, while the out-of-sample estimator uses the previous period's estimate.[17]

For comparison, we also construct MVE portfolios separately for each asset class. The relevant covariance matrices are approximated using asset-class-specific latent factors estimated from (2.4).

To examine the underlying sources of performance and properties of the MVE portfolios, we decompose the conditional MVE portfolio in (6.3) into their asset-class constituents

$$\mathbf{w}_t'\mathbf{R}_{t+1} = \tilde{\boldsymbol{b}}_t'\tilde{\boldsymbol{R}}_{t+1} = \tilde{\boldsymbol{b}}_{Js,t}'\tilde{\boldsymbol{R}}_{t+1}^{s} + \tilde{\boldsymbol{b}}_{Jb,t}'\tilde{\boldsymbol{R}}_{t+1}^{b} + \tilde{\boldsymbol{b}}_{Jo,t}'\tilde{\boldsymbol{R}}_{t+1}^{o}, \tag{6.5}$$

where $\tilde{\boldsymbol{b}}_t = [\tilde{\boldsymbol{b}}_{Js,t}', \tilde{\boldsymbol{b}}_{Jb,t}', \tilde{\boldsymbol{b}}_{Jo,t}']'$ and $\tilde{\boldsymbol{R}}_{t+1} = [\tilde{\boldsymbol{R}}_{t+1}^{s\prime}, \tilde{\boldsymbol{R}}_{t+1}^{b\prime}, \tilde{\boldsymbol{R}}_{t+1}^{o\prime}]'$.

6.2 Performance and Properties of the MVE Portfolio

Panel (i) of Table 13 reports the annualized Sharpe ratios of MVE portfolios constructed using the first ten regressed-PCA factors to estimate $\mathrm{Var}_t[\tilde{\mathbf{R}}_{t+1}]$. The joint MVE portfolio across the three asset classes achieves a Sharpe ratio of 4.22, which is significantly higher than the Sharpe ratios of the asset-class-specific MVE portfolios. Within the MVE portfolio, stock and option constituents have relatively higher Sharpe ratios compared to the corporate bond's.

[17] Imposing the common factor structure reduces the dimensionality problem, but may cause the information loss in the estimation. As a robustness check, we also estimate the covariance matrix directly with characteristic-managed portfolio returns. The in-sample results are reported in Table 14.

Next, we turn to the out-of-sample performance of the joint MVE portfolios. Figure 5 presents the Sharpe ratios of out-of-sample MVE portfolios with the number of latent factors K ranges from 1 to 20. The values are summarized in Table A12. The Sharpe ratios of joint MVE portfolios are generally higher than those of asset-class-specific portfolios, and increase with the number of factors. When $K > 12$, the joint MVE portfolios outperform other asset-class-specific portfolios, with Sharpe ratio of 2.73.

Why does the joint MVE portfolio outperform? We argue that its superior performance stems from the ability to exploit cross-asset interactions that are not available in asset-class-specific optimizations. To examine the sources of these gains, we decompose the joint portfolio into its stock, corporate bond, and option constituents as in , and analyze their mutual correlations as well as their exposures to common factors.

Panel (ii) of Table 13 shows that the joint MVE portfolio is strongly correlated with its stock and option constituents, but not with its bond component. At the same time, the bond constituent is significantly and negatively correlated with both the stock (-0.16) and option (-0.32) constituents. This pattern indicates that bonds serve primarily as a hedge against equity and option risk within the joint portfolio. By combining assets across classes, the MVE portfolio reduces variance through internal hedging, thereby improving efficiency relative to asset-class-specific portfolios.

Panel (iii) of Table 13 further shows that the asset-class constituents have offsetting exposures to the latent common factors. For instance, the stock constituent is negatively correlated with the first factor (-0.30), while the bond constituent is positively correlated (0.36). Similarly, stock and option constituents load with opposite signs on the second factor. As a result, the joint MVE portfolio as a whole has negligible correlations with the common factors. The optimizer effectively chooses loadings that cancel out factor exposures, producing a portfolio whose returns are orthogonal to the sources of systematic variation.

The results highlight the logic behind the mean–variance efficiency. Hedging a factor is attractive when the variance reduction from eliminating its exposure outweighs the loss in expected return from giving up its risk premium. The result that the joint MVE portfolio endogenously eliminates exposures to all common factors indicates that their contribution to systematic variation dominates their associated premia. In this sense, the joint MVE portfolio resembles a "pure-alpha" strategy: its returns are not driven by compensated systematic factor exposures, but by cross-asset reallocations that hedge out such exposures while exploiting idiosyncratic return anomalies.

We also observe the hedging properties in alternative construction methods using the covariance matrix measured directly from characteristic-managed portfolios (Table 14) and in the out-of-sample MVE portfolios (Table A15). Across these specifications, the joint portfolios consistently exhibit low correlations with common factors while maintaining high Sharpe ratios, confirming that the elimination of systematic risk is a structural feature of the optimal portfolio rather than an artifact of the in-sample covariance estimation. The persistence of this pattern in the out-of-sample analysis is particularly notable, as it suggests that the cross-asset pricing errors exploited by the strategy are stable and tradable. Together, the conclusion is robust that the joint MVE portfolio acts as a "pure-alpha" strategy, effectively isolating mispricing by neutralizing under-priced factor risk.

7 Conclusion

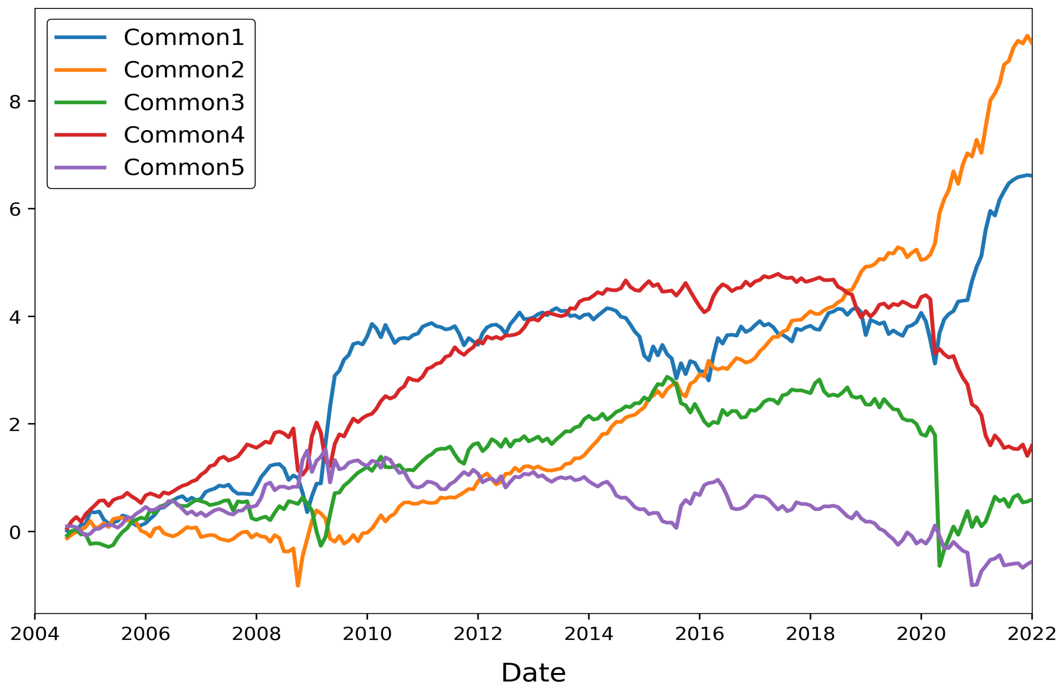
In this paper, we find strong evidence of commonality across major asset classes. Using the regressed-PCA approach, we extract joint latent factors directly from the universe of individual securities spanning equities, corporate bonds, and options. Several of the latent factors exhibit systematic features across markets, consistent with the presence of a common factor structure. However, the common factor structure alone does not fully explain the cross-sectional variation in returns. Portfolios with zero beta loadings on the latent factors deliver substantially higher Sharpe ratios, both in-sample and out-of-sample, indicating the presence of return component orthogonal to common sources of variations.

To assess the portfolio implications of these findings, we construct mean–variance efficient (MVE) portfolios jointly across asset classes using the regressed-PCA-implied conditional covariance. The joint MVE portfolios achieve high Sharpe ratios compared to those optimized within a single market, owing to their ability to exploit cross-asset hedging that offset common factor exposures. The cross-market optimization also highlights the economic value of the latent factors in improving portfolio efficiency and uncovering sources of mispricing.

These findings point to several promising directions for future research. A key question concerns the origin of the "pure-alpha" returns. Determining whether this premium reflects behavioral biases, intermediary constraints, or structural segmentation will help clarify the broader mechanisms behind asset pricing and also market integration. More broadly, the results challenge the conventional view that systematic risk alone governs the risk–return tradeoff. Future work could explore alternative sources of priced risk, and extend the regressed-PCA framework to high-frequency or international settings to better understand how systematic and idiosyncratic risks jointly shape global return dynamics.

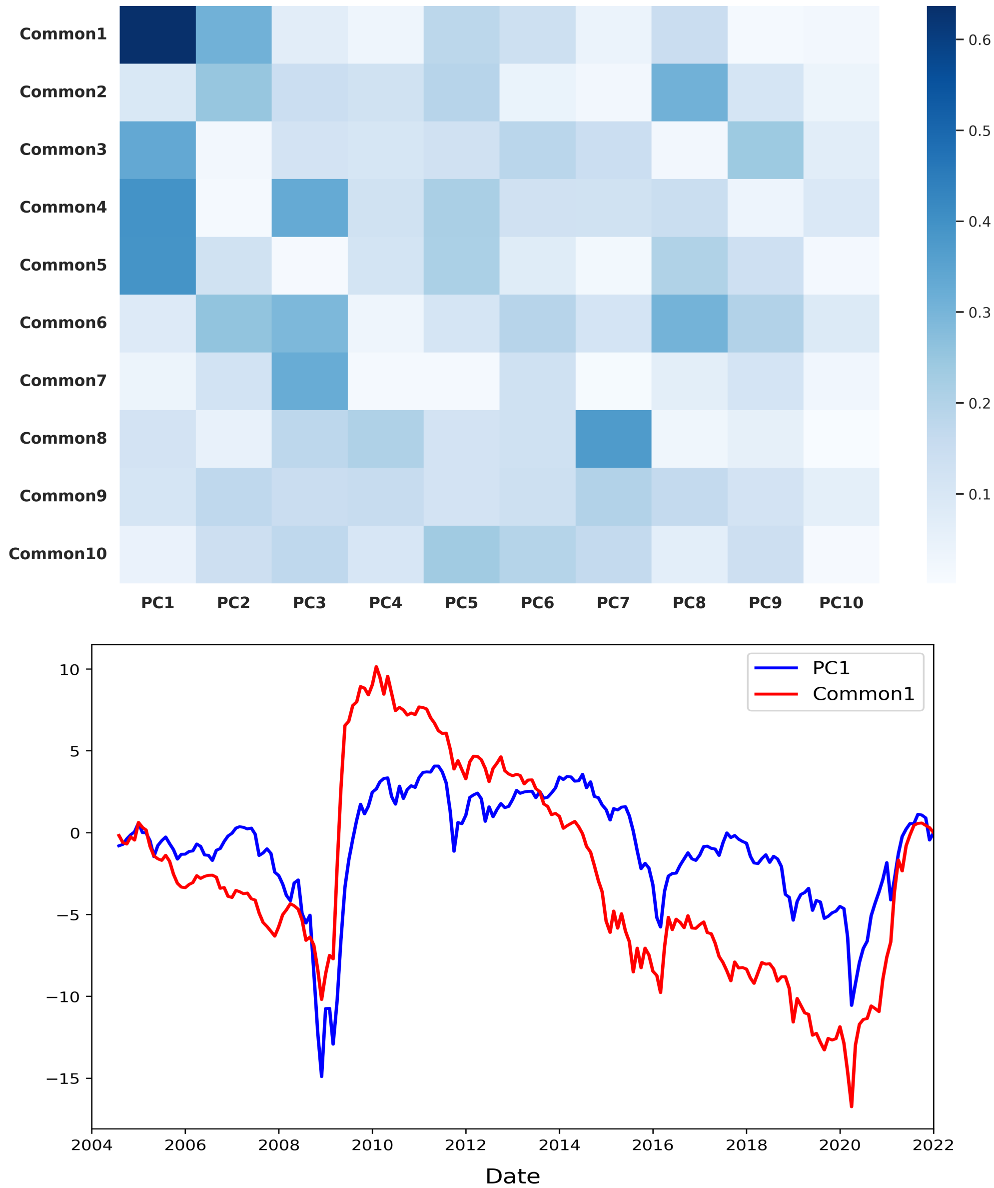
Figures and Tables

Figure 1: Cumulative returns of the first five regressed-PCA common factors



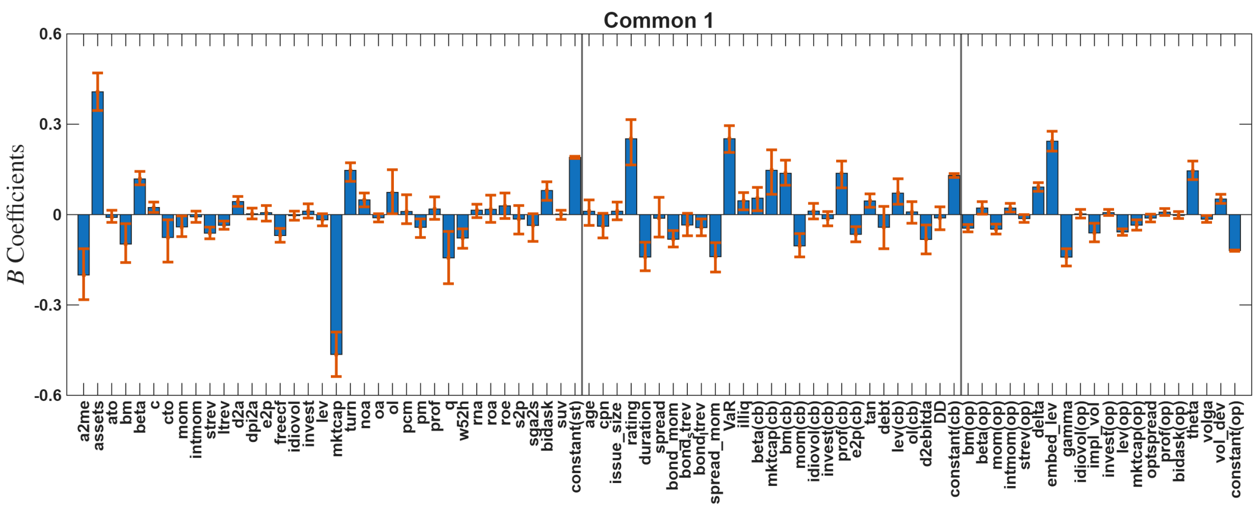
This figure shows the cumulative returns of the first five regressed-PCA common factors, f^C (as defined in (2.7)).

Figure 2: Regressed-PCA common factors *vs.* principal components of observable factors



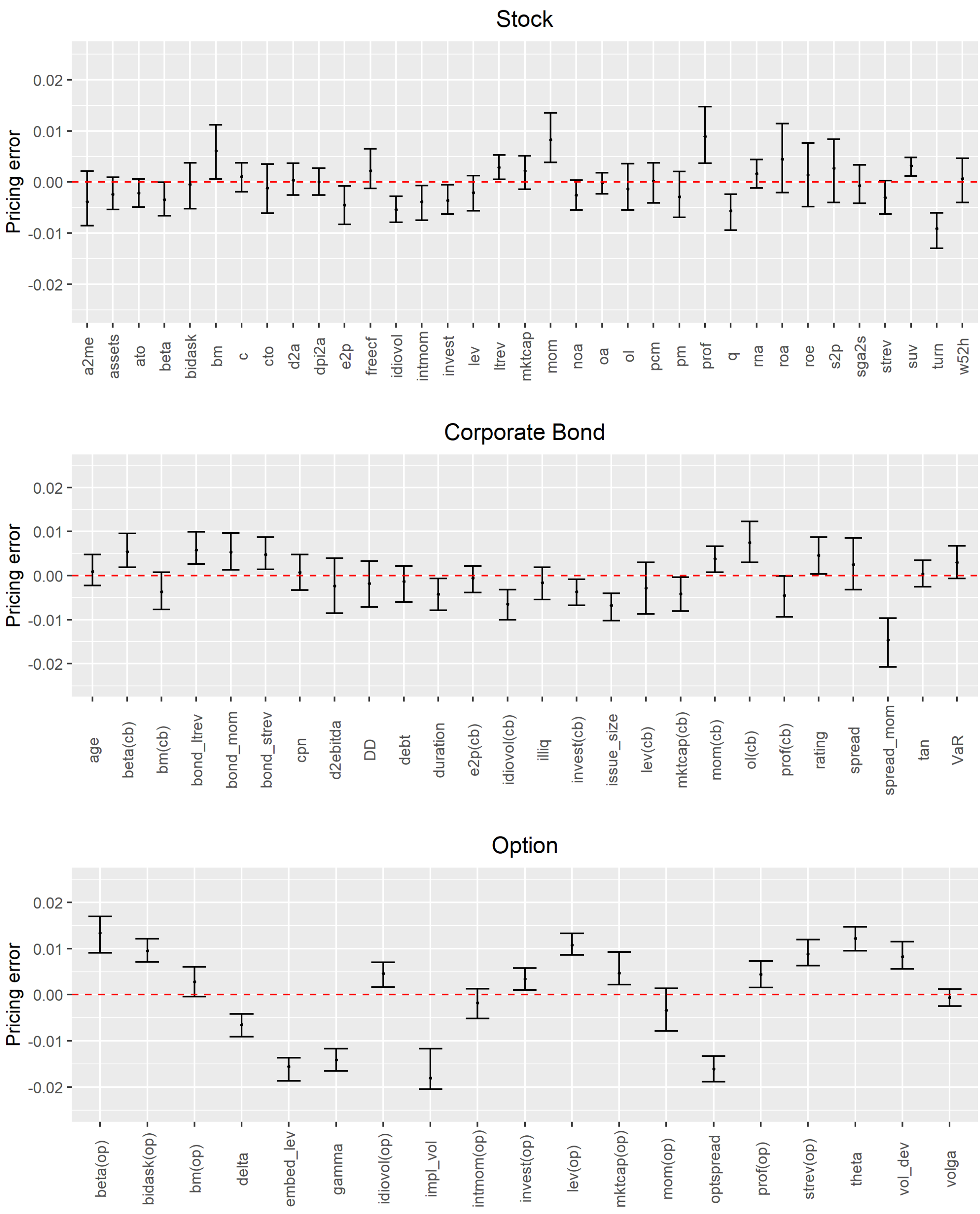
This figure shows the correlations between the regressed-PCA common factors (Common), f^C (as defined in (2.7)), and the principal components (PCs) of the 18 observable factors: six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $MOMB$, $REV*$, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$). See Appendix A2 for details on these observable factors. The top panel reports pairwise correlations, with darker squares indicating higher absolute correlation values. The bottom panel plots the cumulative sums of the first regressed-PCA common factor (red) and the first PC of the observable factors (blue), with both series standardized to have mean zero and variance one.

Figure 3: Estimates of the B coefficients for the first regressed-PCA common factor



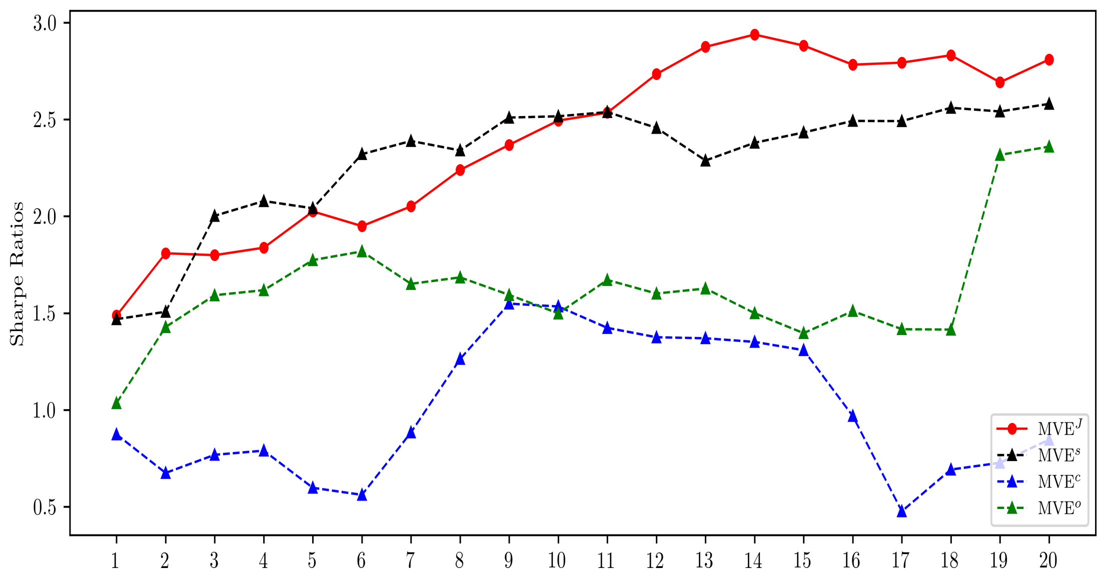
This figure shows the estimated B coefficients (and 95% confidence intervals) for the first regressed-PCA common factor, f^C (as defined in (2.7)). The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

Figure 4: Estimates of the a coefficients in the common factor model with ten factors



This figure shows the estimated a coefficients (and 95% confidence intervals) in the common factor model (as defined in (2.7)) with ten factors. The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

Figure 5: Out-of-sample Sharpe ratios of joint and asset-class MVE portfolios



The figure reports out-of-sample Sharpe ratios for the joint MVE portfolios (solid line), estimated using the common factor model in (2.7), and for the asset-class MVE portfolios (dashed lines), estimated using factor model in equation (2.4) for each asset class separately. The number of factors K ranges from 1 to 20.

Table 1: Summary statistics of monthly returns on stocks, corporate bonds, and options

	No. Obs.	Unique firms	Min No. Obs.	Mean	Std	P10	P25	P50	P75	P90
Stock	738,518	8,082	2,987	1.02%	17.42%	-14.29%	-5.98%	0.43%	6.75%	15.32%
CorpBond	208,652	927	386	0.50%	3.56%	-1.66%	-0.34%	0.34%	1.30%	2.94%
Option	760,836	5,052	1,723	-0.61%	6.96%	-6.41%	-3.39%	-1.20%	1.32%	5.83%

This tables reports the summary statistics of monthly returns on stocks, corporate bonds, and options used throughout the paper. The sample period is from July 2004 to December 2021. The columns represent the number of monthly observation of individual assets, number of unique firms covered through the sample period, the minimum number of observations in each period, the mean of the return, the standard deviation, and 10th percentile, lower quartile, median, upper quartile and 90th percentile of the return distribution, respectively.

Table 2: Correlations between regressed-PCA common factors and observable factors

Common	1	2	3	4	5	6	7	8	9	10
$MKTstock$	0.48***	0.00	0.22***	0.17**	-0.45***	-0.19***	-0.11	0.20***	0.04	-0.10
SMB	0.35***	-0.04	0.21***	0.02	-0.20***	0.01	-0.12*	0.25***	0.05	-0.19***
HML	0.32***	-0.19***	0.21***	0.02	0.10	-0.09	-0.11*	0.04	0.08	-0.20***
RMW	-0.07	0.02	-0.18***	0.01	0.10	0.03	0.05	-0.20***	0.09	0.13*
CMA	0.02	-0.06	-0.13*	-0.09	0.24***	0.15**	-0.05	0.02	-0.06	-0.13*
MOM	-0.64***	0.08	-0.16**	0.00	0.17**	-0.14**	-0.16**	0.09	0.05	0.14**
$MKTbond$	0.41***	0.13*	-0.01	0.58***	-0.39***	-0.09	0.20***	0.13*	-0.11	0.05
CRF	0.60***	-0.25***	0.26***	0.14**	-0.35***	-0.21***	-0.09	0.14**	0.02	-0.10
LRF	0.42***	0.08	0.13*	0.37***	-0.04	0.06	0.20***	-0.10	-0.18***	0.07
LTR	0.46***	-0.06	0.33***	0.24***	-0.09	0.31***	0.16**	-0.00	0.04	-0.13*
$MOMB$	-0.49***	-0.05	-0.27***	-0.36***	0.06	-0.32***	0.02	0.01	-0.01	0.04
$REV*$	0.21***	0.19***	-0.16**	0.17**	-0.13*	0.22***	-0.02	0.19***	0.15**	-0.06
$MKToption$	0.35***	0.23***	0.34***	0.28***	-0.27***	-0.23***	-0.11	0.15**	0.26***	0.07
$LEVEL$	0.36***	0.25***	0.27***	0.48***	-0.35***	-0.18***	-0.08	0.14**	0.17**	0.17**
$SKEW$	0.33***	0.16**	0.21***	0.39***	-0.29***	-0.06	-0.01	-0.03	0.18**	0.16**
$IVOL$	0.19***	0.17**	0.21***	0.07	-0.18***	-0.17**	-0.16**	-0.02	0.17**	-0.02
ILQ	0.21***	-0.01	0.15**	0.02	-0.18***	-0.18**	-0.21***	0.19***	0.05	-0.14**
$VOLDEV$	0.09	0.24***	0.07	0.10	-0.21***	-0.08	-0.08	-0.26***	0.28***	-0.19***

This table reports the correlations between the regressed-PCA common factors, f^C (as defined in (2.7)), and 18 observable factors: six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $BONDMOM$, $REV*$, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$). See Appendix A2 for details on these observable factors. ***: p-value$<1\%$; **: p-value$<5\%$; *: p-value$<10\%$.

Table 3: Regression of regressed-PCA common factors on observable factors

Common	1	2	3	4	5	6	7	8	9	10
(Intercept)	0.03***	0.04***	0.02**	-0.01	0.02**	0.05***	0.03***	0.02***	0.03***	0.04***
	(2.83)	(3.30)	(2.24)	(-0.67)	(2.51)	(8.24)	(3.23)	(3.55)	(5.59)	(6.68)
$MKTstock$	0.02	0.28	0.36	-0.57**	-0.85***	-0.04	-0.62*	-0.03	-0.13	-0.18
	(0.07)	(0.77)	(0.76)	(-2.09)	(-2.66)	(-0.19)	(-1.95)	(-0.17)	(-0.58)	(-1.13)
SMB	0.95**	0.76	0.54	-0.35	-0.30	0.32	-0.12	0.65**	0.17	-0.18
	(2.01)	(1.38)	(1.57)	(-0.93)	(-0.74)	(1.01)	(-0.39)	(2.12)	(0.57)	(-0.76)
HML	-0.03	-0.83*	0.87***	0.98***	1.04***	-0.87***	-0.69*	0.19	0.35	-0.51
	(-0.08)	(-1.87)	(2.98)	(2.74)	(2.59)	(-2.77)	(-1.73)	(0.81)	(1.37)	(-1.60)
RMW	1.12**	-0.54	-0.49	0.04	-0.20	0.41	0.22	-0.93**	0.48	0.37
	(2.12)	(-0.90)	(-0.96)	(0.11)	(-0.42)	(1.10)	(0.44)	(-2.28)	(1.35)	(1.31)
CMA	0.30	0.82	-2.01***	-0.07	0.48	0.75**	-0.40	-0.14	-0.46	-0.56
	(0.43)	(1.21)	(-3.92)	(-0.11)	(1.08)	(1.99)	(-0.80)	(-0.34)	(-1.00)	(-1.12)
MOM	-1.50***	-0.27	-0.06	1.28***	0.35	-0.57***	-0.74	0.19	0.13	-0.06
	(-5.65)	(-0.86)	(-0.20)	(4.87)	(1.31)	(-2.99)	(-1.59)	(0.97)	(0.77)	(-0.38)
$MKTbond$	-0.59	-0.15	-3.53***	3.90***	-2.65***	-1.92***	1.81***	1.31***	-0.67	-0.84
	(-0.63)	(-0.13)	(-4.03)	(5.58)	(-3.94)	(-3.15)	(3.45)	(2.84)	(-0.96)	(-1.43)
CRF	1.87***	-2.85***	-0.56	0.02	-0.71	-1.91***	-0.01	-0.02	-0.21	-0.06
	(4.18)	(-4.33)	(-0.92)	(0.06)	(-1.15)	(-3.62)	(-0.02)	(-0.08)	(-0.55)	(-0.24)
LRF	3.47***	0.40	1.85*	1.29	3.58***	-0.55	-0.13	-1.79**	-1.79	1.26*
	(3.00)	(0.28)	(1.65)	(1.10)	(2.92)	(-0.47)	(-0.13)	(-2.34)	(-1.58)	(1.70)
LTR	1.27	-2.00	1.75**	-0.02	-0.54	4.64***	2.12**	-0.21	1.09	-1.41*
	(0.94)	(-1.54)	(2.07)	(-0.02)	(-0.63)	(5.83)	(2.26)	(-0.29)	(1.32)	(-1.82)
$MOMB$	-0.86	-0.68	-1.67***	-1.64**	-1.39**	-1.88**	1.46**	0.42	0.06	0.12
	(-1.36)	(-0.79)	(-2.60)	(-2.42)	(-2.38)	(-2.47)	(2.16)	(0.80)	(0.13)	(0.41)
REV*	0.84	1.26	-1.74	0.46	-0.11	1.33*	-0.03	1.26***	1.00**	-0.22
	(0.88)	(1.38)	(-1.23)	(0.81)	(-0.16)	(1.75)	(-0.07)	(2.88)	(2.16)	(-0.73)
$MKToption$	3.07*	3.21	3.88**	-2.53	2.97*	-2.86*	2.24	2.49	3.60**	-0.52
	(1.72)	(1.22)	(2.36)	(-1.25)	(1.74)	(-1.68)	(1.28)	(1.44)	(2.47)	(-0.50)
$LEVEL$	-0.73	2.98*	0.70	2.75***	-0.97	-0.41	-0.92	1.90***	-0.76	1.93***
	(-0.65)	(1.84)	(0.81)	(3.35)	(-1.47)	(-0.53)	(-1.02)	(3.02)	(-1.10)	(4.06)
$SKEW$	0.42	-3.83	-0.16	0.06	0.20	4.47***	0.34	-7.66***	1.79	1.60
	(0.17)	(-1.24)	(-0.07)	(0.03)	(0.14)	(2.59)	(0.15)	(-4.34)	(1.21)	(1.60)
$IVOL$	-0.17	0.35	0.04	-0.32	-0.42**	-0.20	-0.37	-0.42*	0.09	0.26
	(-0.63)	(0.95)	(0.13)	(-1.48)	(-1.99)	(-0.66)	(-1.57)	(-1.79)	(0.45)	(1.06)
ILQ	0.20	-0.83*	-0.17	0.13	0.27	0.41	-0.24	0.17	-0.27	-0.43**
	(0.71)	(-1.89)	(-0.49)	(0.67)	(1.42)	(1.60)	(-0.84)	(0.87)	(-1.51)	(-2.54)
$VOLDEV$	-0.26	0.60	-0.48*	0.30	-0.38	-0.16	-0.19	-1.03***	0.60**	-1.12***
	(-1.01)	(1.58)	(-1.80)	(0.89)	(-0.92)	(-0.55)	(-0.55)	(-3.15)	(2.55)	(-4.22)
R^2_{adj}	57.40%	29.26%	31.20%	51.55%	35.89%	45.21%	18.55%	33.28%	19.18%	24.13%
No. Obs.	210	210	210	210	210	210	210	210	210	210

This table reports the regressions of the regressed-PCA common factors, f^C (as defined in (2.7)), on 18 observable factors: six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $BONDMOM$, REV*, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$). See Appendix A2 for details on these observable factors. We report the t-statistics using Newey-West standard errors with four lags in parentheses. ***: p-value$<$ 1%; **: p-value$<$ 5%; *: p-value$<$ 10%.

Table 4: Correlations between common and asset-class-specific regressed-PCA factors

Factors	Stock 1	Stock 2	Stock 3	Stock 4	Stock 5	Stock 6	Stock 7	Stock 8	Stock 9	Stock 10
Common 1	0.85***	0.08	0.12*	-0.14**	0.21***	0.19***	0.01	0.03	0.01	0.03
Common 2	-0.09	0.04	-0.02	-0.07	0.11	-0.13*	-0.10	-0.07	-0.04	-0.04
Common 3	-0.46***	0.37***	0.38***	-0.14**	0.24***	0.27***	-0.01	0.05	-0.00	0.03
Common 4	-0.02	0.42***	-0.43***	-0.21***	0.15**	0.18***	0.09	0.05	-0.00	0.13*
Common 5	0.20***	0.69***	0.13*	0.27***	-0.32***	-0.34***	-0.07	0.01	-0.10	-0.04
Common 6	0.05	-0.35***	0.24***	0.04	-0.27***	0.05	0.22***	0.04	-0.08	0.09
Common 7	-0.01	0.22***	0.15**	-0.14**	-0.36***	0.15**	0.28***	-0.08	0.11	0.02
Common 8	0.03	-0.06	0.63***	0.01	0.24***	-0.17**	-0.04	0.04	-0.05	0.08
Common 9	0.00	0.00	-0.17**	0.78***	0.16**	0.30***	0.05	0.05	-0.01	-0.04
Common 10	0.01	-0.11	-0.26***	-0.28***	-0.16**	-0.17**	-0.09	0.23***	-0.13*	0.01
Factors	**CorpBond 1**	**CorpBond 2**	**CorpBond 3**	**CorpBond 4**	**CorpBond 5**	**CorpBond 6**	**CorpBond 7**	**CorpBond 8**	**CorpBond 9**	**CorpBond 10**
Common 1	0.62***	0.32***	0.24***	0.00	0.06	0.14**	0.04	-0.11	0.07	0.10
Common 2	-0.53***	0.30***	0.02	-0.04	0.11	-0.00	0.12*	-0.11*	0.01	0.09
Common 3	0.51***	0.09	-0.28***	0.01	0.09	-0.19***	0.14**	0.05	-0.18***	-0.00
Common 4	-0.15**	0.61***	0.31***	0.20***	-0.01	0.05	0.06	0.01	-0.11	-0.09
Common 5	-0.11*	-0.07	-0.47***	-0.00	-0.06	0.02	0.24***	0.14*	0.07	-0.10
Common 6	-0.05	0.39***	-0.38***	-0.25***	0.07	-0.26***	0.02	-0.07	0.26***	0.26***
Common 7	-0.04	-0.37***	0.55***	-0.22***	0.12*	-0.28***	0.28***	0.03	0.15**	0.15**
Common 8	-0.09	-0.03	0.13*	0.24***	0.03	-0.05	-0.20***	-0.02	-0.10	0.12*
Common 9	0.01	-0.16**	-0.03	0.11	-0.16**	-0.09	-0.26***	-0.19***	0.01	0.02
Common 10	0.06	-0.27***	-0.14**	0.51***	0.14**	0.06	0.13*	-0.20***	0.20***	0.13*
Factors	**Option 1**	**Option 2**	**Option 3**	**Option 4**	**Option 5**	**Option 6**	**Option 7**	**Option 8**	**Option 9**	**Option 10**
Common 1	0.44***	0.14**	0.07	-0.23***	0.05	0.19***	-0.08	-0.14**	-0.09	0.06
Common 2	0.80***	0.05	0.05	0.16**	0.01	-0.06	0.02	0.02	0.03	-0.05
Common 3	0.24***	0.25***	0.08	-0.12*	-0.19***	-0.07	-0.06	0.13*	-0.01	0.10
Common 4	-0.27***	0.49***	0.46***	-0.22***	-0.07	0.05	-0.04	-0.06	0.04	0.04
Common 5	-0.06	-0.03	-0.08	0.49***	-0.17**	0.05	0.12*	-0.03	-0.03	0.02
Common 6	-0.10	0.61***	-0.48***	0.14**	-0.02	0.05	-0.05	0.10	-0.05	-0.09
Common 7	0.04	0.31***	-0.33***	-0.02	0.10	-0.01	0.05	-0.09	0.10	-0.05
Common 8	-0.08	0.12*	0.42***	0.35***	0.39***	0.03	-0.11*	-0.03	-0.08	0.00
Common 9	0.06	0.25***	0.08	-0.08	0.27***	-0.20***	0.06	-0.00	0.05	-0.04
Common 10	0.06	0.29***	0.17**	0.25***	-0.12*	0.05	0.15**	0.02	0.12*	-0.08

This table reports the correlations between regressed-PCA common factors and regressed-PCA asset-class-specific factors for stocks, corporate bonds, and options. We use the regressed-PCA method introduced in Section 2.2 to extract the common factors as defined in (2.7) and the asset-class-specific factors by applying (2.4) separately to each asset class. ***: p-value$<1\%$; **: p-value$<5\%$; *: p-value$<10\%$.

Table 5: Contribution of asset-class constituents to the regressed-PCA common factors

	Stock	CorpBond	Option
Common1	0.89	0.74	0.51
	[0.57]	[0.29]	[0.14]
Common2	0.25	0.61	0.81
	[0.03]	[0.33]	[0.64]
Common3	0.71	0.60	0.40
	[0.52]	[0.36]	[0.13]
Common4	0.67	0.72	0.70
	[0.29]	[0.37]	[0.35]
Common5	0.84	0.53	0.53
	[0.67]	[0.21]	[0.12]
Common6	0.54	0.66	0.78
	[0.23]	[0.32]	[0.45]
Common7	0.56	0.76	0.47
	[0.24]	[0.57]	[0.20]
Common8	0.72	0.33	0.66
	[0.54]	[0.11]	[0.36]
Common9	0.88	0.35	0.41
	[0.70]	[0.11]	[0.19]
Common10	0.52	0.62	0.44
	[0.30]	[0.45]	[0.25]

This table reports the correlation and variance decomposition of the asset-class constituents of the first ten regressed-PCA common factors. The asset-class constituents are denoted by $\hat{f}_A$, defined in (4.1), where $A \in \{\text{Stock}, \text{CorpBond}, \text{Option}\}$. For each common factor, the first row shows the correlations between the common factor and its asset-class constituents, $\rho(\hat{f}_A, \hat{f}^C)$. The second row shows the variance decomposition of the asset-class constituents in square brackets, defined as $\frac{\text{Cov}(\hat{f}_A, \hat{f}^C)}{\text{Var}(\hat{f}^C)}$.

Table 6: Correlations between regressed-PCA common factors and macroeconomic and financial variables

Common	1	2	3	4	5	6	7	8	9	10
Core inflation	-0.05	-0.13*	0.16**	-0.05	-0.00	-0.14**	-0.08	-0.00	0.03	0.01
Δc	-0.06	-0.10	0.48***	0.06	-0.03	-0.08	-0.23***	0.11	-0.16**	-0.02
$\Delta INDPRO$	-0.22***	-0.17**	0.40***	0.03	0.05	-0.03	-0.21***	0.05	-0.15**	-0.01
$\Delta(EPU)$	-0.16**	0.08	-0.36***	-0.17**	0.13*	0.05	0.17**	-0.14**	0.03	0.12*
$\Delta(FFR)$	0.01	-0.25***	0.14**	0.09	-0.22***	-0.38***	-0.11	0.03	-0.14**	-0.04
$\Delta(TERM)$	0.22***	-0.07	0.22***	-0.19***	0.23***	0.10	-0.13*	-0.10	0.10	-0.15**
$\Delta(DEF)$	-0.08	-0.17**	0.00	-0.21***	-0.05	-0.19***	0.12*	-0.05	0.11	0.17**
$\Delta(VIX)$	-0.40***	-0.17**	-0.07	-0.29***	0.46***	0.09	0.06	-0.00	-0.03	-0.05
$\Delta(FINU)$	-0.41***	-0.17**	-0.18**	-0.30***	0.15**	0.17**	0.04	-0.21***	0.07	-0.15**
$\Delta(MACU)$	-0.28***	0.04	-0.14**	-0.21***	0.17**	0.25***	0.12*	-0.11	0.13*	0.02
HKM	0.48***	-0.15**	0.29***	0.04	-0.33***	-0.17**	-0.10	0.12*	0.00	-0.16**
LIQ	-0.00	0.00	0.04	0.13*	-0.02	-0.06	-0.25***	0.07	-0.09	-0.09

This table reports the correlations between the regressed-PCA common factors, f^C (as defined in (2.7)), and a set of macroeconomic and financial variables. The macroeconomic and financial variables include: core inflation; consumption growth (Δc); growth in industrial production ($\Delta INDPRO$); change in economic policy uncertainty, $\Delta(EPU)$; change in the federal funds rate, $\Delta(FFR)$; change in the term spread, $\Delta(TERM)$; change in the credit spread, $\Delta(DEF)$; change in the VIX index, $\Delta(VIX)$; change in financial uncertainty, $\Delta(FINU)$; change in macroeconomic uncertainty, $\Delta(MACU)$; the intermediary capital factor (HKM); and the liquidity factor (LIQ). See Section 4.2 for details on these variables. ***: p-value$< 1\%$; **: p-value$< 5\%$; *: p-value$< 10\%$.

Table 7: Regression of regressed-PCA common factors on macroeconomic and financial variables

Common	1	2	3	4	5	6	7	8	9	10
Core inflation	0.02	-0.00	0.05	-0.06	0.06	-0.09*	-0.03	0.01	0.10	0.07
	(0.56)	(-0.01)	(1.0)	(-0.92)	(1.19)	(-1.8)	(-0.45)	(0.15)	(1.21)	(1.06)
	[0.00]	[0.02]	[0.02]	[0.02]	[0.00]	[0.05]	[0.01]	[0.00]	[0.08]	[0.02]
Δc	0.07	0.21*	0.23**	-0.01	-0.05	-0.03	-0.22	0.14	-0.21	-0.03
	(0.93)	(1.76)	(2.3)	(-0.06)	(-0.45)	(-0.2)	(-1.44)	(1.22)	(-1.0)	(-0.24)
	[0.02]	[0.03]	[0.28]	[0.01]	[0.01]	[0.01]	[0.17]	[0.06]	[0.19]	[0.01]
$\Delta INDPRO$	-0.33***	-0.21	0.24*	0.00	0.05	0.17	0.03	-0.10	0.02	0.11
	(-3.99)	(-1.63)	(1.68)	(0.0)	(0.49)	(1.11)	(0.23)	(-0.71)	(0.1)	(0.89)
	[0.12]	[0.08]	[0.20]	[0.01]	[0.02]	[0.03]	[0.11]	[0.02]	[0.10]	[0.01]
$\Delta(EPU)$	-0.03	0.15	-0.16**	-0.05	0.04	-0.03	0.00	-0.01	-0.18	0.11
	(-0.5)	(1.64)	(-2.21)	(-0.66)	(0.52)	(-0.38)	(0.03)	(-0.1)	(-1.51)	(1.12)
	[0.03]	[0.04]	[0.14]	[0.05]	[0.02]	[0.01]	[0.05]	[0.06]	[0.09]	[0.09]
$\Delta(FFR)$	-0.10	-0.21*	-0.09	0.06	-0.11	-0.33**	-0.05	-0.15*	-0.06	-0.03
	(-1.33)	(-1.7)	(-1.1)	(0.65)	(-1.32)	(-2.28)	(-0.5)	(-1.95)	(-1.07)	(-0.44)
	[0.02]	[0.22]	[0.02]	[0.01]	[0.07]	[0.44]	[0.03]	[0.05]	[0.11]	[0.01]
$\Delta(TERM)$	0.18***	-0.07	0.18**	-0.10	0.23***	-0.01	-0.20***	-0.18**	0.10	-0.11
	(2.69)	(-0.9)	(2.45)	(-1.32)	(3.68)	(-0.08)	(-3.28)	(-1.98)	(1.3)	(-1.29)
	[0.10]	[0.03]	[0.12]	[0.12]	[0.15]	[0.02]	[0.17]	[0.13]	[0.09]	[0.13]
$\Delta(DEF)$	0.01	-0.21	0.13*	-0.15**	-0.11	-0.21*	0.05	-0.02	0.13	0.14
	(0.13)	(-1.29)	(1.65)	(-2.03)	(-1.42)	(-1.87)	(0.57)	(-0.31)	(1.56)	(1.35)
	[0.00]	[0.16]	[0.02]	[0.15]	[0.02]	[0.18]	[0.04]	[0.01]	[0.13]	[0.16]
$\Delta(VIX)$	-0.04	-0.17*	0.01	-0.25*	0.43***	-0.02	0.11	0.27*	-0.08	-0.07
	(-0.42)	(-1.84)	(0.13)	(-1.72)	(5.05)	(-0.18)	(1.12)	(1.81)	(-0.6)	(-0.8)
	[0.13]	[0.13]	[0.01]	[0.27]	[0.45]	[0.01]	[0.02]	[0.15]	[0.03]	[0.04]
$\Delta(FINU)$	-0.20***	-0.19*	-0.13	-0.15	-0.22**	0.06	-0.09	-0.25**	0.02	-0.29***
	(-2.68)	(-1.8)	(-1.61)	(-1.09)	(-2.35)	(1.0)	(-1.11)	(-2.33)	(0.2)	(-2.95)
	[0.17]	[0.14]	[0.04]	[0.21]	[0.05]	[0.05]	[0.01]	[0.32]	[0.02]	[0.28]
$\Delta(MACU)$	-0.22**	0.04	0.13	-0.03	0.08	0.18*	0.04	0.01	0.09	0.09
	(-2.34)	(0.36)	(1.24)	(-0.18)	(0.9)	(1.66)	(0.33)	(0.06)	(1.05)	(1.12)
	[0.11]	[0.02]	[0.02]	[0.07]	[0.03]	[0.15]	[0.02]	[0.04]	[0.10]	[0.02]
HKM	0.32**	-0.20**	0.21	-0.18	-0.18**	-0.02	0.07	0.24***	-0.02	-0.18*
	(2.22)	(-2.24)	(1.59)	(-1.44)	(-2.36)	(-0.11)	(0.39)	(2.79)	(-0.22)	(-1.69)
	[0.29]	[0.14]	[0.12]	[0.06]	[0.18]	[0.05]	[0.02]	[0.15]	[0.01]	[0.17]
LIQ	-0.02	0.05	-0.03	0.04	0.08	-0.02	-0.26***	0.03	-0.05	-0.09
	(-0.2)	(0.95)	(-0.44)	(0.3)	(1.15)	(-0.24)	(-3.63)	(0.45)	(-0.62)	(-1.18)
	[0.01]	[0.01]	[0.00]	[0.03]	[0.01]	[0.00]	[0.35]	[0.02]	[0.05]	[0.05]
R^2_{adj}	38.60%	16.26%	32.41%	13.84%	28.48%	18.41%	9.62%	5.39%	2.60%	8.96%
No.Obs	210	210	210	210	210	210	210	210	210	210

This table reports the regressions of regressed-PCA common factors, f^C (as defined in (2.7)), on a set of macroeconomic and financial variables. The macroeconomic and financial variables include: core inflation; consumption growth (Δc); growth in industrial production ($\Delta INDPRO$); change in economic policy uncertainty, $\Delta(EPU)$; change in the federal funds rate, $\Delta(FFR)$; change in the term spread, $\Delta(TERM)$; change in the credit spread, $\Delta(DEF)$; change in the VIX index, $\Delta(VIX)$; change in financial uncertainty, $\Delta(FINU)$; change in macroeconomic uncertainty, $\Delta(MACU)$; the intermediary capital factor (HKM); and the liquidity factor (LIQ). See Section 4.2 for details on these variables. We report the t-statistics using Newey-West standard errors with four lags in parentheses. The Shapley-Owen R^2's are in square brackets. The regressed PCA factors and the macroeconomic variables are standardized using the time-series standard deviation. ***: p-value $< 1\%$; **: p-value $< 5\%$; *: p-value $< 10\%$.

Table 8: Regression of the asset-class components of the first regressed-PCA common factor on macroeconomic and financial variables

	Common1 - Stock	Common1 - CorpBond	Common1 - Option
Core inflation	-0.01	0.02	0.07
	(-0.11)	(0.46)	(0.58)
Δc	-0.09	0.15*	**0.27****
	(-1.08)	(1.72)	(1.97)
$\Delta INDPRO$	**-0.30*****	-0.15*	-0.29**
	(-2.74)	(-1.86)	(-2.48)
$\Delta(EPU)$	0.03	**-0.16****	0.04
	(0.44)	(-2.35)	(0.45)
$\Delta(FFR)$	-0.07	0.01	**-0.21****
	(-1.02)	(0.17)	(-2.06)
$\Delta(TERM)$	0.12*	**0.19*****	0.09
	(1.86)	(2.79)	(1.08)
$\Delta(DEF)$	-0.07	**0.15*****	-0.03
	(-1.17)	(2.99)	(-0.23)
$\Delta(VIX)$	0.04	-0.03	**-0.22****
	(0.38)	(-0.40)	(-2.23)
$\Delta(FINU)$	-0.16**	-0.08	**-0.23****
	(-2.47)	(-0.96)	(-2.30)
$\Delta(MACU)$	-0.19*	**-0.19****	-0.07
	(-1.82)	(-2.19)	(-0.56)
HKM	0.24**	**0.38****	0.05
	(2.19)	(2.28)	(0.58)
LIQ	0.02	-0.06	-0.03
	(0.29)	(-0.95)	(-0.45)
R^2_{adj}	24.42%	41.16%	22.89%
No.Obs	210	210	210

This table reports the regressions of the asset-class constituents of the first regressed-PCA common factors (as defined in (4.1)) on a set of macroeconomic and financial variables. The macroeconomic and financial variables include: core inflation; consumption growth (Δc); growth in industrial production ($\Delta INDPRO$); change in economic policy uncertainty, $\Delta(EPU)$; change in the federal funds rate, $\Delta(FFR)$; change in the term spread, $\Delta(TERM)$; change in the credit spread, $\Delta(DEF)$; change in the VIX index, $\Delta(VIX)$; change in financial uncertainty, $\Delta(FINU)$; change in macroeconomic uncertainty, $\Delta(MACU)$; the intermediary capital factor (HKM); and the liquidity factor (LIQ). See Section 4.2 for details on these variables. The regressed PCA factors and the macroeconomic variables are standardized using the time-series standard deviation. t-statistics are reported in parentheses. The split regressed PCA factors and the macroeconomic variables are standardised using the time series standard deviation. We report the t-statistics using Newey-West standard errors with four lags. For each variable, we highlight in bold the coefficient with the highest absolute value that is statistically significant across the three regressions. ***: p-value$<$ 1%; **: p-value$<$ 5%; *: p-value$<$ 10%.

Table 9: Forecasting and nowcasting of macro-financial variables with regressed-PCA factors

	Panel A: Forecasting			Panel B: Nowcasting		
	ξ	(t)	R^2_{adj}	ξ^{now}	(t)	R^2_{adj}
Core inflation	1.91	(6.35)	0.21	0.54	(1.88)	0.02
$\Delta(FFR)$	0.23	(2.48)	0.03	0.38	(4.03)	0.09
Δc	0.88	(2.11)	0.02	-0.09	(-0.28)	-0.01
$\Delta INDPRO$	0.40	(1.89)	0.02	-0.00	(-0.01)	-0.01
$\Delta(MACU)$	0.05	(1.06)	0.00	0.07	(1.15)	0.00
$\Delta(DEF)$	0.09	(0.98)	-0.00	-0.12	(-1.59)	0.01
$\Delta(TERM)$	0.12	(0.89)	-0.00	0.50	(4.42)	0.11
$\Delta(FINU)$	0.02	(0.42)	-0.01	0.52	(5.66)	0.17
LIQ	-0.02	(-0.16)	-0.01	-0.01	(-0.19)	-0.01
$\Delta(VIX)$	-0.12	(-0.65)	-0.00	0.17	(4.38)	0.11
$\Delta(EPU)$	-0.08	(-1.24)	0.00	-0.03	(-0.30)	-0.01
HKM	-0.25	(-1.84)	0.02	0.84	(11.05)	0.45

This table reports the forecasting and nowcasting regressions of macro-financial variables using the regressed-PCA common factors. Panel A tabulates the forecasting regression coefficients ξ in (4.4), and Panel B the nowcasting regression coefficients ξ^{now} in (4.7).

Table 10: In-sample and out-of-sample performance (R^2's) of the common factor model

(i) All the returns on three asset classes

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	15.21	6.11	25.96	5.18	12.56
2	25.15	7.27	26.55	8.95	13.65
3	32.91	8.88	26.85	12.46	14.29
4	40.16	11.46	26.98	11.80	14.50
5	46.02	13.34	27.19	11.45	14.79
6	52.12	14.26	27.42	11.15	15.14
7	56.59	14.76	27.52	10.01	15.31
8	60.40	15.51	27.69	12.45	15.63
9	63.87	16.31	27.84	13.25	15.91
10	67.01	16.76	27.95	13.11	16.09
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\bar{R}}$	
1-10	23.97	8.90	8.86	24.83	

(ii) Stock Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	21.85	6.27	9.49	12.06	8.13
2	22.57	6.29	10.06	12.52	8.59
3	32.97	7.04	10.95	14.09	9.48
4	38.11	7.41	11.18	14.30	9.65
5	48.35	9.27	11.25	13.93	9.70
6	52.09	9.56	11.55	14.39	10.00
7	54.47	9.77	11.78	14.50	10.26
8	59.07	10.74	11.79	14.33	10.25
9	65.15	11.12	11.96	14.30	10.43
10	67.73	11.51	12.00	14.25	10.45
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\bar{R}}$	
1-10	0.22	0.71	0.04	18.64	

(iii) Corporate Bond Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	13.45	11.21	2.40	−27.78	−6.20
2	23.70	11.58	0.52	−31.78	−12.08
3	32.58	13.74	2.14	−27.16	−11.54
4	40.98	23.30	2.85	−27.23	−11.93
5	45.08	27.79	4.46	−27.98	−9.35
6	49.94	29.35	11.29	−19.45	−1.63
7*	58.40	32.20	13.07	−17.79	0.46
8	59.73	32.99	14.03	−18.28	1.09
9	60.92	33.74	16.60	−15.09	4.65
10	65.12	33.99	17.43	−14.70	5.37
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\bar{R}}$	
1-10	2.22	5.48	1.67	47.68	

(iv) Option Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	8.82	5.40	29.30	5.47	12.97
2*	29.73	7.66	29.93	9.38	14.59
3	33.15	9.97	30.10	12.94	15.12
4	41.88	13.76	30.20	12.26	15.30
5	44.07	15.35	30.41	11.92	15.48
6	54.30	16.76	30.50	11.49	15.54
7	57.40	17.26	30.56	10.28	15.56
8	62.69	17.81	30.74	12.82	15.99
9	65.20	19.00	30.83	13.61	16.20
10	67.97	19.53	30.94	13.46	16.41
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\bar{R}}$	
1-10	28.55	9.12	11.24	27.80	

This table reports the in-sample and out-of-sample performance of the common factor model in (2.7). Panels report R^2's for (i) all returns, (ii) stocks, (iii) corporate bonds, and (iv) options. K is the number of factors; * marks the estimator of K that maximizes the ratio of adjacent eigenvalues. R^2_K captures the variation explained in characteristic-managed portfolios by PCA factors. $R^2_{\bar{R}}$ is the R^2 from the Fama–MacBeth cross-sectional regression. R^2 is the total in-sample R^2 defined in (2.9). R^2_O, $R^2_{T,N,O}$, and $R^2_{N,T,O}$ measure out-of-sample predictability, see (2.10) - (2.12). $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit based on factors approximated by (2.13), see (2.14)–(2.16). All R^2's are reported in percentage terms.

Table 11: Sharpe ratios of the regressed-PCA factors

(i) Common

	1	2	3	4	5	6	7	8	9	10
In Sample	**0.83**	**1.23**	0.41	0.43	0.10	**1.03**	**0.78**	**0.95**	**1.21**	**1.28**
Out of Sample w/o α	0.18	**1.46**	0.06	**0.92**	**-0.75**	**0.60**	-0.11	-0.27	-0.05	0.04
Out of Sample w/ α	**0.49**	**2.50**	0.01	**0.58**	-0.25	0.09	**-0.48**	0.16	-0.08	-0.31

(ii) Stock

	1	2	3	4	5	6	7	8	9	10
In Sample	0.47	0.09	0.24	0.30	0.16	0.11	0.12	**0.54**	0.26	0.39
Out of Sample w/o α	-0.11	-0.11	0.48	**-0.50**	-0.02	0.39	-0.01	-0.02	-0.38	-0.05
Out of Sample w/ α	0.11	-0.32	-0.13	-0.14	0.22	0.29	0.12	-0.23	-0.06	-0.28

(iii) Corporate Bond

	1	2	3	4	5	6	7	8	9	10
In Sample	0.01	**0.51**	0.25	0.24	0.47	0.23	**0.63**	0.05	0.01	**0.75**
Out of Sample w/o α	**-0.64**	**0.97**	-0.38	-0.11	**0.98**	0.32	-0.11	**0.60**	**-0.89**	**0.53**
Out of Sample w/ α	**-0.73**	**0.76**	-0.48	-0.07	**1.03**	0.14	**-0.54**	0.37	**-0.80**	**0.76**

(iv) Option

	1	2	3	4	5	6	7	8	9	10
In Sample	**1.37**	**2.30**	0.20	**1.29**	**1.35**	0.41	0.35	**1.55**	**0.74**	**1.73**
Out of Sample w/o α	**2.50**	**-0.48**	-0.32	**0.63**	0.41	0.14	**0.62**	0.43	-0.29	**1.03**
Out of Sample w/ α	**2.78**	-0.42	-0.32	**0.90**	0.40	0.35	**0.94**	**0.74**	-0.20	**1.13**

This table reports the in-sample and out-of-sample Sharpe ratios of the regressed-PCA common factors (2.7) in Panel (i), and regressed-PCA asset-class-specific factors (2.4) for stocks, corporate bonds, and options in Panel (ii)-(iv), respectively. We show Sharpe ratios of two types of out-of-sample factors, the one excludes α as in (2.13) , and the one does not as in (5.1). The reported Sharpe ratios are annualized, and those with t-statistics greater than 2.0 are highlighted in bold print.

Table 12: Out-of-sample performance of the pure-alpha strategy for the common factor model

(i) All the returns on three asset classes

K	μ_α	σ_α	SR_α
1	7.50	3.50	2.14
2	3.33	3.25	1.02
3	3.29	3.18	1.03
4	3.05	3.20	0.95
5	3.07	3.20	0.96
6	3.06	3.03	1.01
7	3.61	2.94	1.23
8	3.27	2.36	1.39
9	3.26	2.16	1.51
10	3.52	1.79	1.96

(ii) Stock Returns

K	μ_α	σ_α	SR_α
1	0.27	0.72	0.37
2	0.18	0.66	0.28
3	0.24	0.60	0.39
4	0.29	0.63	0.45
5	0.32	0.60	0.52
6	0.25	0.62	0.41
7	0.26	0.53	0.49
8	0.36	0.62	0.58
9	0.54	0.64	0.85
10	0.51	0.62	0.82

(iii) Corporate Bond Returns

K	μ_α	σ_α	SR_α
1	0.71	0.67	1.06
2	−0.51	0.97	−0.52
3	−0.50	0.99	−0.51
4	−0.42	1.01	−0.42
5	−0.39	1.00	−0.39
6	−0.49	1.06	−0.46
7	−0.31	1.13	−0.28
8	−0.24	0.94	−0.26
9	−0.21	0.75	−0.28
10	−0.12	0.70	−0.17

(iv) Option Returns

K	μ_α	σ_α	SR_α
1	6.52	3.42	1.91
2	3.65	2.97	1.23
3	3.55	2.92	1.22
4	3.18	2.94	1.08
5	3.14	2.93	1.07
6	3.29	2.71	1.21
7	3.66	2.62	1.40
8	3.15	2.05	1.53
9	2.94	1.89	1.55
10	3.14	1.61	1.95

This table reports the out-of-sample performance of pure-alpha strategy in (2.17) for the common factor model in (2.7). K denotes the number of factors specified. μ_α, σ_α and SR_α are the annualized means (%), standard deviations (%), and Sharpe ratios of the pure-alpha strategy.

Table 13: In-sample Sharpe ratios and correlations of MVE portfolios with the covariance matrix approximated by factors

(i) Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE and its constituents	4.22	2.08	1.05	2.81
Asset-class MVE	-	2.98	1.58	2.64

(ii) Correlations between constituents in joint MVE				
	Joint	Stock	CorpBond	Option
Joint	-	0.50***	0.03	0.76***
Stock	-	-	-0.16**	-0.03
CorpBond	-	-	-	-0.32***

(iii) Correlations between constituents in joint MVE and common factors				
	Joint	Stock	CorpBond	Option
Common 1	-0.09	-0.30***	0.36***	-0.08
Common 2	0.07	-0.18***	0.00	0.19***
Common 3	-0.04	-0.09	0.07	-0.02
Common 4	-0.04	0.07	0.38***	-0.26***
Common 5	-0.02	-0.01	-0.23***	0.09
Common 6	-0.02	0.03	-0.11	0.00
Common 7	-0.07	-0.05	-0.07	-0.01
Common 8	-0.08	-0.09	0.11	-0.08
Common 9	0.15**	0.13*	-0.04	0.10
Common 10	0.10	0.12*	0.04	0.01

This table reports the in-sample performance of MVE portfolios constructed from the first ten estimated regressed-PCA common factors (2.7) and the factor model in (2.4) for each asset class separately. Panel (i) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class MVE portfolios. Panel (ii) reports correlations among the constituents of the joint MVE portfolio. Panel (iii) reports correlations between the constituents of the joint MVE portfolio and the common factors. We approximate the covariance matrix of characteristic-managed portfolios using (6.4).

Table 14: In-sample Sharpe ratios and correlations of MVE portfolios with the covariance matrix estimated with characteristic-managed portfolios

(i) Sharpe ratios

	Joint	Stock	CorpBond	Option
Joint MVE and its constituents	8.04	3.12	1.52	4.67
Asset-class MVE	-	4.24	2.37	4.90

(ii) Correlations between constituents in joint MVE

	Joint	Stock	CorpBond	Option
Joint	-	0.40***	0.07	0.63***
Stock	-	-	-0.07	-0.33***
CorpBond	-	-	-	-0.33***

(iii) Correlations between constituents in joint MVE and common factors

	Joint	Stock	CorpBond	Option
Common 1	-0.00	-0.07	0.22***	-0.06
Common 2	0.21***	-0.10	-0.03	0.28***
Common 3	0.10	-0.10	-0.01	0.17**
Common 4	0.08	0.06	0.39***	-0.14**
Common 5	-0.02	-0.05	-0.30***	0.16**
Common 6	0.07	-0.06	-0.38***	0.28***
Common 7	0.06	-0.24***	0.29***	0.10
Common 8	0.09	-0.11*	0.15**	0.10
Common 9	0.27***	0.22***	-0.15**	0.16**
Common 10	0.20***	0.05	0.01	0.15**

This table reports the in-sample performance of MVE portfolios constructed from the first ten estimated regressed-PCA common factors (2.7) and the factor model in (2.4) for each asset class separately. Panel (i) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class MVE portfolios. Panel (ii) reports correlations among the constituents of the joint MVE portfolio. Panel (iii) reports correlations between the constituents of the joint MVE portfolio and the common factors. We estimate the covariance matrix directly with characteristic-managed portfolio returns.

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Appendix A1 Filters and Characteristics

This section describes the data filters and characteristics used to model returns on corporate bonds and options. We also reference studies that apply these characteristics in empirical work or detail their construction.

For corporate bonds, we use the dataset constructed by Dickerson, Robotti, and Rossetti (2023) and apply the same set of filters. In particular, the authors impose two prominent filtering criteria with respect to the issue size: (1) remove investment grade bonds of less than $150 ($250) million outstanding prior to (after) November 2004, and (2) remove high-yield bonds that have less than $100 ($250) million outstanding prior to (after) September 2016. Also, different from the WRDS bond database which the returns are truncated at 100%, the authors adjust the returns that are over 100% with returns computed from ICE quote database. Besides, the authors follow the standard data preparation procedure to clean the corporate bond data.[18] They collapse the transaction-level prices into daily prices by taking the par volume-weighted average of intraday prices (Bessembinder, Kahle, Maxwell, and Xu, 2008). They remove transaction records in TRACE Enhanced that are canceled and adjust records that are subsequently corrected or reversed. They eliminate bonds with non-standard transactions which are labeled as when-issued (WIS_FL), locked-in ($LCKD_IN_IND$), have special sales conditions ($SPCL_TRD_FL$), or have trading-volume of less than $100,000.[19] They also exclude bonds with non-standard issuance, i.e., bonds that are issued through private placement (*private_placement*) or under the 144A rule (*rule_144a*) and bonds that do not trade in US dollars. They further drop bonds that are structured notes, mortgage backed or asset backed, agency backed, or equity linked, as well as convertible bonds, bonds that trade under $5 or above $1000, bonds that have a floating

[18]See Dick-Nielsen (2009), Dick-Nielsen (2014), Nozawa (2017), and van Binsbergen and Schwert (2021)

[19]Dickerson, Robotti, and Rossetti (2023) mention that the volume filter of $100,000 can significantly reduce the noises from potential retail trades.

or zero coupon rate, and bonds that have less than one year to maturity. They restrict the bond's interest payment frequency between monthly and annual.

We use 26 characteristics for corporate bonds. The first 12 characteristics are on the contract level, and the next 14 characteristics are on the stock level.

1. **Bond age** (*age*): Following Israel, Palhares, and Richardson (2017). Years since the date the bond was issued.

2. **Coupon** (*cpn*): Following Chung, Wang, and Wu (2019). Coupon payment adjusted for payment frequency.

3. **Rating** (*rating*): Numerical credit rating from 1 to 22, based on S&P rating and Moody's rating.

4. **Issue size** (*issue_size*): The offering amount outstanding of the bond at issuance.

5. **Duration** (*duration*): Following Israel, Palhares, and Richardson (2017) and van Binsbergen and Schwert (2021). The sensitivity of bond value to credit spread.

6. **Spread** (*spread*): The yield spread, defined as the yield-to-maturity in excess of the one-month treasury yield.

7. **Mom 6m** (*bond_mom*): Following Gebhardt, Hvidkjaer, and Swaminathan (2005a). The most recent 6-2 cumulative bond returns, with a minimum period of 3 months.

8. **Mom 6m Spread** (*spread_mom*): Following Kelly, Palhares, and Pruitt (2022). The credit spread 6 months earlier minus current log spread.

9. **Value-at-risk** (VaR): Following Bai, Bali, and Wen (2019). The 2nd lowest credit excess return (in excess of one-mo Treasury bill rate) over the past 24 months, with a minimum of 12 months.

10. **Short-term reversal** (*bond_strev*): bond return reversal from Dickerson, Robotti, Rossetti (2023)

11. **Long-term reversal** (*bond_ltrev*): 48-minus-12-month reversal from Dickerson, Robotti, Rossetti (2023)

12. **Bond illiquidity** (*illiq*): MMN-adjusted bond illiquidity as per Bao, Pan, and Wang (2011) and Dickerson, Robotti, Rossetti (2023)

13. **Tangibility** (*tan*): Following Hahn and Lee (2009), defined as (0.715 $\times$ total receivables (RECT) + 0.547 $\times$ inventories (INVT) + 0.535 $\times$ property, plant and equipment (PPENT) + cash and short-term investments (CHE)) / total assets (AT).

14. **Total debt** (*debt*): Defined as the sum of long-term debt and debt in current liabilities.

15. **Debt-to-EBITDA** (*d2ebitda*): Total debt divided by EBITDA.

16. **Distance-to-default** (*DD*): Merton model implied firm-specific distance to default, following Gilchrist and Zakrajšek (2012).

17-26. **Book leverage** (*lev*)**, Market beta** (*beta*)**, Market capitalization** (*mktcap*)**, Book-to-market ratio** (*bm*)**, Gross profitability** (*prof*)**, Investment** (*invest*)**, Idiosyncratic volatility** (*idiovol*)**, Stock momentum** (*mom*)**, Operating leverage** (*ol*)**, and Earnings-to-price ratio** (*e2p*): The data on these stock-level characteristics are from Freyberger, Höppner, Neuhierl, and Weber (2022). The above stock-level characteristics are also included in a number of studies such as Gebhardt, Hvidkjaer, and Swaminathan (2005b), Choi and Kim (2018), and Kelly, Palhares, and Pruitt (2022) to examine the effect of stock on corporate bond pricing.

For options, we apply the following filters. The option price is defined as the midpoint of the bid and ask quotes. First, to match the stock sample, we include only options on common stocks. Second, to reduce microstructure noise, we keep options where the bid price is positive, the bid is below the ask, the midpoint is at least \$0.125, and the bid–ask spread is between the minimum tick size (\$0.05 for options priced below \$3 and \$0.10 otherwise) and \$5. Third, we retain only at-the-money options that expire in 1–12 months, have absolute delta between 0.375 and 0.625 and with positive trading volume at time t, focusing on the most liquid contracts. Fourth, we keep standard options that expire on the third Friday of the month, have non-missing and positive implied volatility, and have non-missing deltas between –1 and 1. Fifth, because equity options are American style, we control for early exercise by dropping options with a low time value share— $\frac{F-V}{F} < 5\%$—where F is the option price and V is intrinsic value: $\max(S-K,0)$ for calls and $\max(K-S,0)$ for puts (Frazzini and Pedersen, 2021). Finally, we impose standard no-arbitrage conditions (Zhan, Han, Cao, and Tong, 2022).

To make the portfolio implementation as realistic as possible and further avoid look-ahead bias, we use prevailing market quotes to unwind positions at the end of the holding period (the last trading day of the following month), $t+1$, unless clear recording errors are present (e.g., bid prices of 998 or 999).[20]

We use 19 characteristics to model option returns: seven at the contract level and twelve at the stock level.

1. **Implied volatility (*impl_vol*)**: Following Büchner and Kelly (2022), the American option implied volatility is computed by the Ivy DB database of OptionMetrics using the binomial tree model (Cox, Ross, and Rubinstein, 1979).

2. **Delta (*delta*)**: Following Büchner and Kelly (2022), the delta of the option contract computed by OptionMetrics.

[20]See Duarte, Jones, Mo, and Khorram (2023) and Duarte, Jones, and Wang (2023), who also highlight the impact of look-ahead bias in out-of-sample option-based strategies.

3. **Gamma** (*gamma*): Following Büchner and Kelly (2022), the gamma of the option contract computed by OptionMetrics.

4. **Theta** (*theta*): Following Büchner and Kelly (2022), the theta of the option contract computed by OptionMetrics.

5. **Volga** (*volga*): Following Büchner and Kelly (2022), the volga of the option contract, the sensitivity of vega to changes in volatility, i.e.,

$$volga = \frac{\partial Vega}{\partial \sigma}.$$

   This is not provided by OptionMetrics, and hence we compute it by using standard Black-Scholes pricing formula with zero dividend rate.

6. **Embedded leverage** (*embed_lev*): Following Büchner and Kelly (2022) and Frazzini and Pedersen (2021), the embedded leverage of the option contract is the amount of market exposure per unit of committed capital, defined as

$$\Omega = \left| \frac{\Delta \cdot S}{F} \right|,$$

   where Δ is the option delta, S is the underlying price and F is the option price.

7. **Option illiquidity** (*optspread*): Following Christoffersen, Goyenko, Jacobs, and Karoui (2018), Bali, Beckmeyer, Moerke, and Weigert (2021) and Goyenko and Zhang (2021), the option illiquidity is the ratio of the bid-ask spread to the mid-point of bid and ask for each option contract.

8. **Volatility deviation** (*vol_dev*): Following Zhan, Han, Cao, and Tong (2022), Cao and Han (2013), Goyenko and Zhang (2021), and Goyal and Saretto (2009). The volatility deviation is defined as the difference between the historical realized volatility

and the ATM option implied volatility. The historical realized volatility is the standard deviation of daily realized returns over the past 360 days (this is extracted from the *Historical_Volatility File* in OptionMetrics), and the ATM option implied volatility is the average of the implied volatility of one at-the-money call (with delta equal to 0.5) and one at-the-money put (with delta equal to -0.5) which have 30 days to maturity (these are extracted from the *Volatility_Surface File* in OptionMetrics).

9-19. **Market beta (*beta*), Market capitalization (*mktcap*), Book-to-market ratio (*bm*), Gross profitability (*prof*), Investment (*invest*), Idiosyncratic volatility (*idiovol*), Book leverage (*lev*), Average daily bid-ask spread (*bidask*), Momentum (*mom*), Intermediate momentum (*intmom*), Short-term reversal (*strev*), and Book leverage (*lev*)**: The data on these stock-level characteristics are from Freyberger, Höppner, Neuhierl, and Weber (2022). These characteristics have been demonstrated to have a significant impact on option returns, for example, idiosyncratic volatility (*idiovol*) by Cao and Han (2013) and Zhan, Han, Cao, and Tong (2022), average daily bid-ask spread (*bidask*) and momentum (*mom*) by Bali, Beckmeyer, Moerke, and Weigert (2021) and Goyenko and Zhang (2021).

Appendix A2 Common Factor Structure from Observable Factors

Is there a common factor structure among stocks, corporate bonds, and options? To explore this, we start with a straightforward econometric approach: applying Principal Component Analysis (PCA) to observable pricing factors. These pricing factors have been well-established in the asset pricing literature for different asset classes. The rationale behind this exercise is that if the various asset classes are integrated, then the observable factors that explain their returns should exhibit a shared component structure. We opt for PCA as it is specifically designed to extract common components from multiple time-series data.

We first construct a matrix of observable factors, standardized to zero mean and unit variance:

$$P = [P_{stock} \quad P_{corpbond} \quad P_{option}]$$

The PCA transforms the matrix of observable factors P into principal components F and eigenvector weights B:

$$P_{T\times L} = F_{T\times K} B_{K\times L} + \epsilon_{T\times L}.$$

We use $L = 18$ observable factors:

- Six stock factors: five factors from Fama and French (2015) ($MKTstock$, SMB, HML, RMW, CMA) and the momentum factor from Carhart (1997) (MOM);
- Six corporate bond factors: bond market factor ($MKTbond$), credit risk factor (CRF), liquidity risk factor (LRF), bond momentum ($MOMB$), bond return reversal (REV^*), and long-term reversal (LTR) from Bai, Bali, and Wen (2019) and Dickerson, Mueller, and Robotti (2023);[21]

[21] We remove the downside risk factor (DRF) since it is highly correlated with $MKTbond$ after lead-lag correction. See Dickerson, Mueller, and Robotti (2023) for more details on the lead-lag correction for factors.

- Six option factors: volatility level ($LEVEL$), and moneyness skewness ($SKEW$) factors from Büchner and Kelly (2022), option idiosyncratic volatility ($IVOL$) and illiquidity (ILQ) factors from Zhan, Han, Cao, and Tong (2022), and option-market ($MKToption$) and volatility deviation factors ($VOLDEV$) from Goyal and Saretto (2009).[22]

The sample period is from July 2004 to December 2021, starting when corporate bond factors become available.

The blue line in the bottom panel of Figure 2 shows the cumulative sum of the first principal component of the 18 observable factors. This component exhibits a systematic pattern aligned with major market downturns, including the 2008 financial crisis, the 2015–2016 global equity selloff, the December 2018 market decline, and the 2020 COVID crisis. This pattern suggests that the first component may reflect underlying macroeconomic or fundamental risks that affect multiple asset classes.

To assess the extent of commonality, we compute the explained variance ratio for the first ten principal components in Table A1. The first component explains 30.51% of the variation in the 18 observable factors, while the next two account for 12.52% and 9.57%, respectively. Collectively, the first ten components explain 88% of the total variation, indicating a significant common structure among pricing factors across asset classes.

[22] We exclude the maturity slope factor ($SLOPE$) from Büchner and Kelly (2022) since it is highly correlated with $LEVEL$.

Table A1: Explained variance ratios of principal components

	PC1	2	3	4	5	6	7	8	9	10
Variance Ratio (%)	30.51	12.52	9.57	7.00	6.56	5.82	5.17	4.21	3.89	2.79

This table reports the explained variance ratios for the first ten principal components of 18 observable pricing factors: six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $MOMB$, $REV*$, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$).

A natural next question is whether these principal components also explain the observable factors within each of the three asset classes. A sufficient condition for a component to be considered "common" is that it has comparable explanatory power for the factors in all asset classes. In contrast, if most of its explanatory power comes from, say, stock factors, it should be regarded as a stock-specific component rather than a common one. Distinguishing common components, which capture shared variation across asset classes, from asset-specific components, which primarily capture variation in a single class, is essential for interpretation.

To examine this, we compute, for each principal component F^k, its marginal R^2 for the factors in each asset class. Specifically, we fit the observable factors P by each principal component F^k and its corresponding weight B^k:

$$\hat{P}_t^k = [\hat{P}_{t,stock}^k \quad \hat{P}_{t,corpbond}^k \quad \hat{P}_{t,option}^k] = B^{k\prime} F_t^k$$

where $\hat{P}^k$ denotes the fitted factors from the kth principal component. We can compute the marginal R^2's of component k for asset class $g \in \{stock, corpbond, option\}$ as:

$$R_{k,g}^2 = 1 - \frac{\sum_t (P_g^k - \hat{P}_g^k)^2}{\sum_{g,t} (P_g^k)^2}.$$

Table A2: Marginal R^2 of principal components on factors across asset classes

Marginal R^2 (%)	PC1	2	3	4	5	6	7	8	9	10
Stock	20.47	16.99	10.18	17.26	2.78	1.62	3.22	6.66	1.63	7.54
Corporate Bond	31.72	3.82	15.15	1.18	4.71	13.32	2.85	4.65	7.97	0.76
Option	44.91	16.27	4.04	2.67	14.64	2.71	1.80	1.10	0.72	0.07

This table reports the marginal R^2's of the first ten principal components (PCs) of 18 observable pricing factors in explaining the observable factors from three asset classes, stocks, corporate bonds, and options, separately.

Table A2 reports the results. The first principal component explains factors across all three asset classes, suggesting it captures a common factor. Specifically, it accounts for 20.47% of the variation in stock factors, 31.72% in corporate bond factors, and 44.91% in option factors.

The PCA analysis of observable factors highlights an important insight: there exists a common component that explains variations across the three asset classes. There is also suggestive evidence that this component is systematically related to economic cycles. Nonetheless, these results are limited because they are based on aggregated, observable factors rather than individual assets. To address this limitation, the main focus of the paper is to identify common factors directly from individual asset returns, which provides a more detailed view of the underlying factor structure across stocks, corporate bonds, and options.

Appendix A3 Beta Loadings of the Regressed-PCA Common Factors

In this appendix, we provide a detailed discussion of the relative weights of the characteristics in the beta loadings of the regressed-PCA common factors.

We focus on the first regressed-PCA common factor. Figure 3 reports the estimated B coefficients with 95% confidence intervals. The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

On the stock side, book assets and market capitalization dominate the beta loadings. These two characteristics have weights of similar magnitude but opposite signs, reflecting a "value" or "leverage" factor involved in the beta loadings. Interestingly, book-to-market ratio has a negligible weight, suggesting that the effects of book assets and market capitalization capture the variation typically associated with book-to-market. This finding aligns with Kelly, Pruitt, and Su (2019), who report that the first IPCA factor's beta is driven by high book assets and low market equity.

On the corporate bond side, ratings, duration, bond momentum, spread momentum and Value-at-Risk (VaR) contribute to the beta loadings of the first common factor. The exposures to ratings and duration are consistent with the literature showing that credit and duration risks significantly influence the bond risk premium. Duration carries a negative weight, indicating that higher-duration securities earn lower average returns, consistent with the negative term structure of risk premia documented in van Binsbergen, Brandt, and Koijen (2012) and van Binsbergen and Koijen (2017). The bond momentum loading is negative and marginally significant; in line with Jostova, Nikolova, Philipov, and Stahel (2013), this suggests that positive bond momentum is primarily associated with return anomalies rather than risk exposure. The VaR loading is positive and significant, consistent with Dickerson, Mueller, and Robotti (2023), who show that downside risk factors correlate strongly with bond market returns. We also find VaR highly correlated with bond return volatility (correlation > 0.9), indicating it may serve as a proxy for volatility.

On the option side,characteristics related to embedded leverage and option Greeks (gamma and theta) have prominent beta loadings, along with certain underlying stock characteristics such as book-to-market and momentum. Embedded leverage, which measures an option's return magnification relative to the underlying asset, carries a significant positive beta loading, reflecting that options with higher leverage increase investors' risk exposure and thus require higher expected returns. Furthermore, consistent with Frazzini and Pedersen (2021), Figure 4 shows that embedded leverage contributes negatively to the alpha of option returns, consistent with the idea that higher risk exposure reduces risk-adjusted returns.

Figures A1–A3 present the beta loadings for the second through tenth regressed-PCA common factors for completeness.

Appendix A4 Regressed-PCA Factors and Macro Factors from Ludvigson and Ng (2009)

In this appendix, we show how our regressed-PCA common factors are related to the macro factors constructed by Ludvigson and Ng (2009). The sample period is from July 2004 to December 2021. Tables A3 and A4 present the correlations and regression results, respectively.

Ludvigson and Ng (2009) provide detailed interpretations of their factors. F_1 is a“real” factor, loading heavily on measures of employment, production, capacity utilization, and new manufacturing orders, with minimal relation to prices or financial variables. F_2 is associated with several interest rate spreads and is highly correlated with the single forward-rate factor in Cochrane and Piazzesi (2005). Both F_3 and F_4 are inflation factors, while F_8 is a stock market factor.

From Tables A3 and A4, we find that the first regressed-PCA common factor is related to the real factor (F_1), the interest rate factor (F_2), and one of the inflation factors (F_4). The second common factor is significantly related to the stock market factor (F_8).

Appendix A5 Robustness Checks

This appendix presents alternative model specifications and robustness analyses for the main results.

We examine factor models estimated separately for each asset class using equation (2.4). We also consider restricted versions of the factor models obtained by imposing $\alpha = 0$ in equation (2.1). The corresponding matrix representations are

$$R_t = Z_{t-1} B f_t + \xi_t, \tag{7.1}$$

$$\mathbf{R}t = \mathbf{Z}t - 1\mathbf{B}f^{C}t + \boldsymbol{\xi}t, \tag{7.2}$$

which are the restricted counterparts of models (2.4) and (2.7), respectively. We estimate (7.1) for each asset class separately and (7.2) for the common factors across asset classes.

We then assess robustness of the out-of-sample analyses by extending the sample to include the post-2020 period, which covers the COVID-19 pandemic and the GameStop episode. The extended sample spans July 2004 to December 2021, with the first 60 months used for initial training.

Appendix A5.1 In-Sample and Out-of-Sample R^2's and Performance of the Pure-Alpha Strategy

Table A6 reports the out-of-sample fit of the common factor model in (2.7), based on the out-of-sample factors approximated by equation (5.1). Table A5 reports the in-sample and out-of-sample R^2's of the restricted common factor model in (7.2). Tables A7 and A8 report the in-sample and out-of-sample R^2's of the unrestricted factor model in (2.4) and the restricted factor model in (7.1), respectively, estimated separately for each asset class. Table A9 shows the performance of the pure-alpha strategy based on the factor models (2.4) for each asset class.

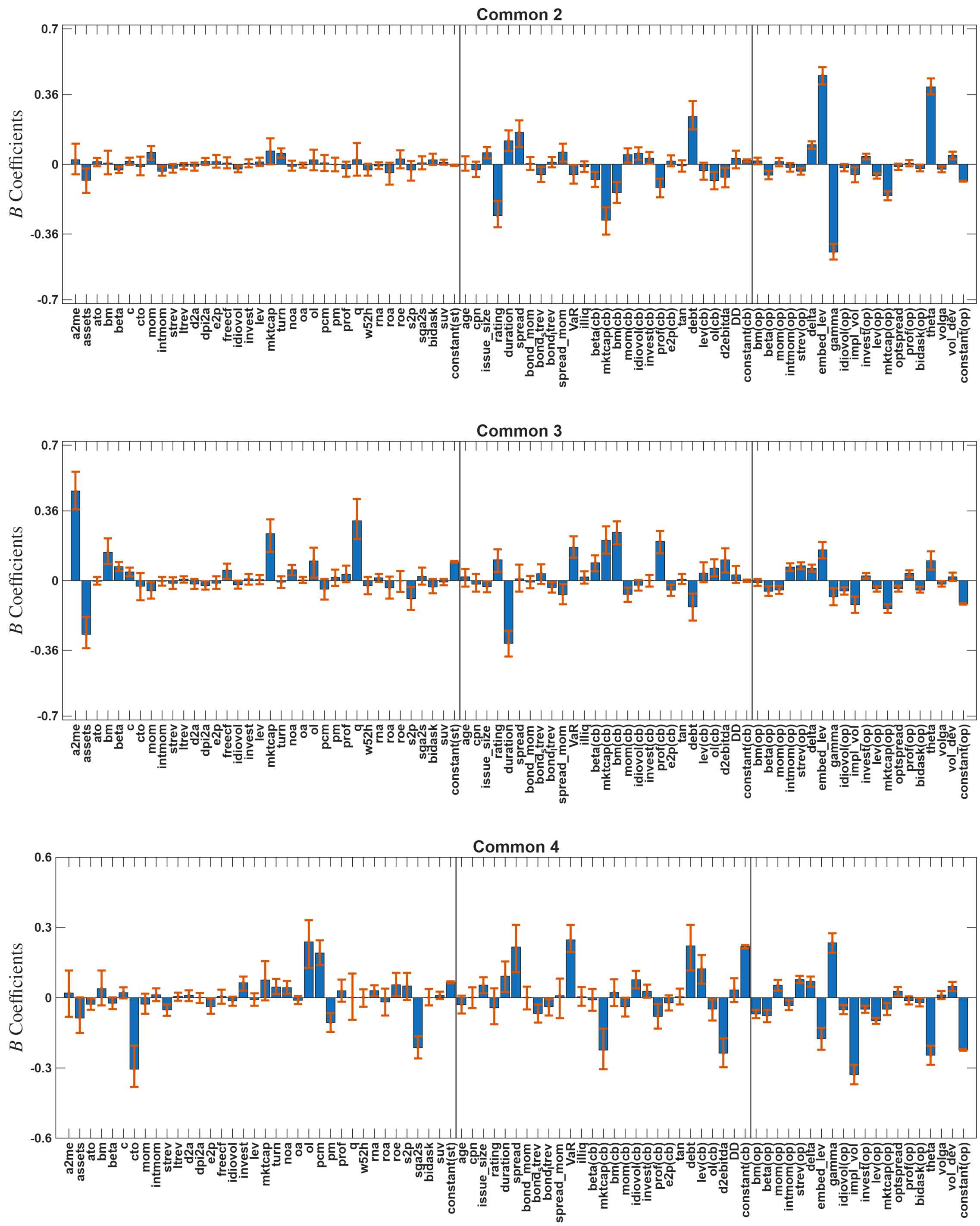
We next extend the out-of-sample analysis to include the post-2020 period. The results are reported under Case (1) in Table A10. We further report results based on trimmed options data, excluding observations below the 1st percentile or above the 99th percentile of the return distribution in each period (Case (2)). As shown in Case (1), extreme option returns during highly volatile episodes reduce the model's out-of-sample fit for stocks and corporate bonds but improve it for options, as the estimation emphasizes matching option return outliers. The performance of the pure-alpha trading strategy remains largely stable. In Case (2), trimming improves the out-of-sample fit across all asset classes by mitigating the influence of extreme option returns. However, this trimming introduces look-ahead bias, as volatile option returns are excluded ex ante, leading to inflated out-of-sample Sharpe ratios for the options strategy (above 3).

Appendix A5.2 MVE Portfolios

Table A11 reports the in-sample performance of MVE portfolios estimated from the restricted models. The Sharpe ratio for the joint MVE portfolio is 2.03, substantially lower than that from the unrestricted model reported in Table 13. Table A12 presents out-of-sample Sharpe ratios of MVE portfolios as the number of factors K varies from 1 to 20. These results are also illustrated in Figure 5. The MVE portfolios are constructed from the unrestricted factor models, using data from July 2004 to December 2019. Table A13 extends the analysis through December 2021, while Table A14 reports the results for the restricted models. For both in-sample and out-of-sample, the unrestricted model consistently delivers higher Sharpe ratios than the restricted model, suggesting that allowing for nonzero intercepts improves portfolio performance.

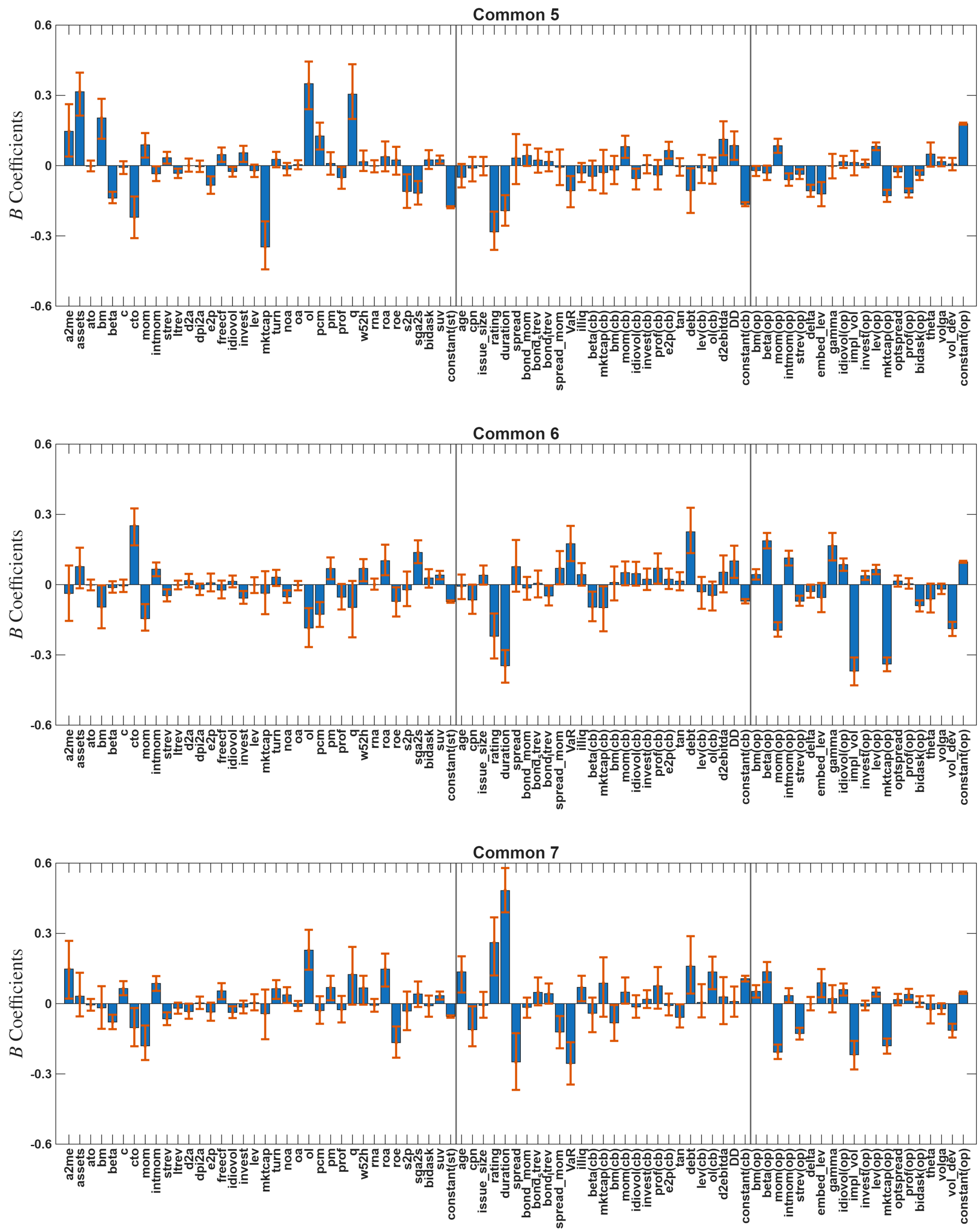
Table A15 reports the correlations among out-of-sample MVE portfolios constructed from the unrestricted models using data from July 2004 to December 2019. Table A16 extends the analysis through December 2021, while Table A17 reports the results for the restricted models.

Figure A1: Estimates of the B coefficients for the second to fourth regressed-PCA common factors



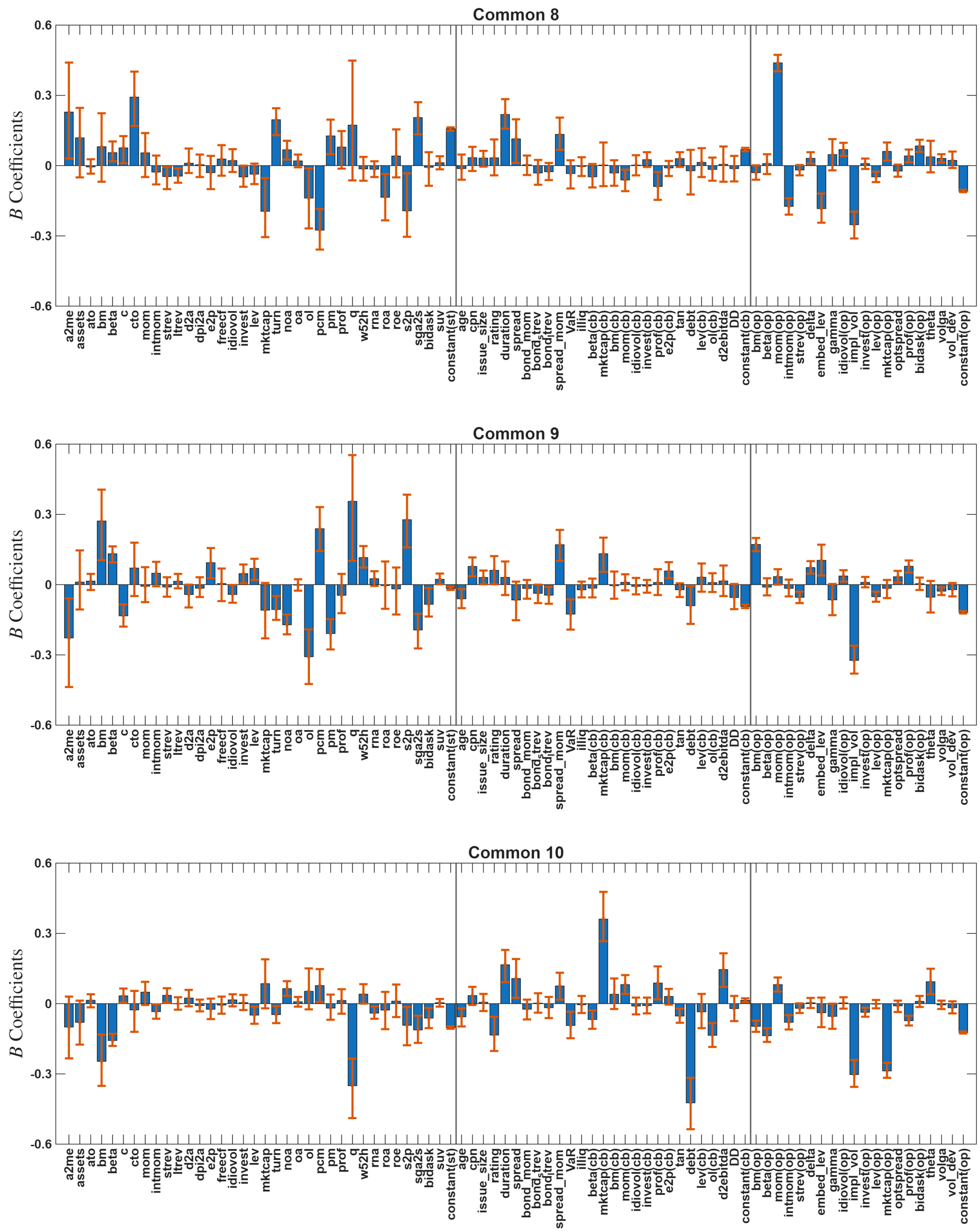
This figure shows the estimated B coefficients (and 95% confidence intervals) for the second to fourth regressed-PCA common factors, f^C (as defined in (2.7)). The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

Figure A2: Estimates of the B coefficients for the fifth to seventh regressed-PCA common factors



This figure shows the estimated B coefficients (and 95% confidence intervals) for the fifth to seventh regressed-PCA common factors, f^C (as defined in (2.7)). The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

Figure A3: Estimates of the B coefficients for the eighth to tenth regressed-PCA common factors



This figure shows the estimated B coefficients (and 95% confidence intervals) for the eighth to tenth regressed-PCA common factors, f^C (as defined in (2.7)). The coefficients are obtained using the regressed-PCA method described in Section 2.2, and the confidence intervals are computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2023).

Table A3: Correlations between regressed-PCA common factors and macro factors from Ludvigson and Ng (2009)

Common	1	2	3	4	5	6	7	8	9	10
F1	0.15**	0.07	-0.17**	0.01	0.14**	0.34***	0.32***	-0.13*	0.05	0.07
F2	0.30***	-0.05	0.17**	0.28***	-0.18***	-0.11	0.02	0.06	-0.10	-0.05
F3	-0.09	0.11	0.06	-0.01	0.10	0.10	0.14**	0.05	-0.12*	0.03
F4	-0.11	-0.06	0.04	-0.00	0.15**	0.18***	0.04	-0.21***	0.04	-0.03
F5	0.07	0.08	0.18**	0.08	-0.02	-0.07	0.01	0.17**	-0.16**	0.06
F6	0.17**	0.03	0.10	-0.06	0.17**	0.04	0.01	0.13*	-0.07	0.09
F7	0.25***	-0.21***	0.20***	0.20***	-0.30***	-0.31***	-0.13*	0.10	0.03	-0.07
F8	0.09	-0.25***	0.11	0.20***	-0.00	-0.07	-0.05	-0.03	-0.12*	0.09

This table reports the correlations between the regressed-PCA common factors, f^C (as defined in (2.7)), and eight macro factors from Ludvigson and Ng (2009). The sample period is from July 2004 to December 2021. ***: p-value$<$ 1%; **: p-value$<$ 5%; *: p-value$<$ 10%.

Table A4: Regression of regressed-PCA common factors on macro factors from Ludvigson and Ng (2009)

Common	1	2	3	4	5	6	7	8	9	10
F1	0.35***	0.09	-0.17	0.09	-0.00	0.24***	0.37***	0.00	0.03	0.11*
	(2.59)	(0.92)	(-1.34)	(0.67)	(-0.02)	(3.11)	(3.19)	(0.0)	(0.35)	(1.67)
	[0.22]	[0.04]	[0.17]	[0.02]	[0.05]	[0.39]	[0.61]	[0.07]	[0.02]	[0.20]
F2	0.37***	0.07	0.15	0.39**	-0.19*	-0.02	0.24*	0.12	-0.27**	-0.08
	(4.06)	(0.94)	(1.57)	(2.44)	(-1.78)	(-0.21)	(1.93)	(0.87)	(-2.52)	(-0.92)
	[0.29]	[0.02]	[0.16]	[0.44]	[0.13]	[0.03]	[0.06]	[0.06]	[0.24]	[0.07]
F3	0.11	0.18	0.10	0.23*	-0.06	0.06	0.32**	0.14	-0.31***	-0.06
	(0.89)	(1.3)	(0.71)	(1.67)	(-0.62)	(0.4)	(2.33)	(1.33)	(-3.08)	(-0.47)
	[0.03]	[0.09]	[0.04]	[0.05]	[0.03]	[0.03]	[0.14]	[0.08]	[0.27]	[0.03]
F4	-0.25***	-0.21**	0.15	-0.16	0.26**	0.07	-0.26***	-0.25***	0.14	-0.02
	(-2.65)	(-2.2)	(1.26)	(-1.02)	(2.27)	(0.6)	(-2.65)	(-2.63)	(1.17)	(-0.24)
	[0.08]	[0.10]	[0.07]	[0.03]	[0.17]	[0.09]	[0.08]	[0.41]	[0.06]	[0.03]
F5	0.02	0.01	0.02	-0.11	0.02	-0.04	-0.10	0.07	0.09	0.12
	(0.33)	(0.1)	(0.22)	(-0.98)	(0.24)	(-0.37)	(-1.09)	(0.67)	(1.05)	(1.45)
	[0.04]	[0.04]	[0.11]	[0.04]	[0.01]	[0.02]	[0.03]	[0.18]	[0.17]	[0.13]
F6	0.14*	-0.03	0.17**	-0.06	0.23***	0.07	-0.03	0.05	-0.05	0.06
	(1.81)	(-0.34)	(2.3)	(-0.63)	(2.82)	(1.03)	(-0.27)	(0.77)	(-0.69)	(0.84)
	[0.09]	[0.01]	[0.12]	[0.02]	[0.21]	[0.03]	[0.00]	[0.09]	[0.04]	[0.17]
F7	0.25***	-0.19*	0.18*	0.12	-0.23***	-0.25**	-0.11	0.08	0.09	-0.04
	(5.15)	(-1.79)	(1.88)	(1.07)	(-3.34)	(-2.05)	(-0.89)	(0.84)	(1.33)	(-0.61)
	[0.23]	[0.27]	[0.26]	[0.17]	[0.39]	[0.39]	[0.07]	[0.08]	[0.04]	[0.11]
F8	0.05	-0.23***	0.07	0.19***	0.03	-0.02	-0.02	-0.06	-0.12	0.09
	(0.72)	(-3.71)	(1.01)	(3.54)	(0.43)	(-0.34)	(-0.21)	(-0.99)	(-1.6)	(1.22)
	[0.02]	[0.44]	[0.06]	[0.22]	[0.00]	[0.01]	[0.01]	[0.03]	[0.16]	[0.25]
R^2_{adj}	24.61%	10.17%	9.76%	12.73%	14.35%	15.55%	13.79%	5.69%	3.96%	-0.46%
No.Obs	210	210	210	210	210	210	210	210	210	210

This table reports the regressions of regressed-PCA common factors, f^C (as defined in (2.7)), on eight macro factors from Ludvigson and Ng (2009). We report the t-statistics using Newey-West standard errors with four lags in parentheses. The Shapley-Owen R^2's are in square brackets. The regressed PCA factors and the macro factors are standardized using the time-series standard deviation. ***: p-value$<$ 1%; **: p-value$<$ 5%; *: p-value$<$ 10%.

Table A5: In-sample and out-of-sample performance (R^2's) of the restricted common factor model

(i) All the returns on three asset classes

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	15.80	6.20	24.05	5.34	8.96	26.08	8.85	12.81
2	26.16	7.54	24.03	8.30	8.91	26.62	10.88	13.85
3	33.90	8.86	24.00	8.59	8.84	26.88	13.92	14.42
4	41.13	10.21	24.02	7.14	8.88	27.05	14.92	14.70
5	47.25	12.75	24.00	6.92	8.87	27.29	14.84	15.01
6	53.09	14.18	23.94	6.92	8.81	27.43	15.18	15.22
7	57.62	14.41	23.92	7.30	8.77	27.60	15.64	15.57
8	61.47	15.26	23.95	8.85	8.82	27.75	15.77	15.88
9	64.78	16.01	23.93	9.12	8.79	27.87	15.89	16.10
10	67.67	16.32	23.94	9.08	8.80	27.98	16.07	16.27

(ii) Stock Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	18.95	5.71	0.42	1.19	−0.35	8.62	11.57	7.11
2	23.15	6.11	0.38	1.14	−0.30	10.28	12.89	8.86
3	32.80	6.76	0.33	1.11	−0.38	11.12	14.44	9.71
4	36.74	6.90	0.35	1.06	−0.31	11.32	14.59	9.85
5	41.54	7.91	0.19	0.57	−0.31	11.35	14.30	9.85
6*	52.50	9.45	−0.03	0.04	−0.14	11.66	14.73	10.17
7	53.78	9.52	−0.03	0.11	−0.13	11.72	14.79	10.24
8	57.07	10.00	0.16	0.53	−0.07	11.94	14.95	10.44
9	63.50	10.97	0.07	0.37	−0.13	12.08	15.00	10.59
10	68.18	11.41	0.06	0.37	−0.15	12.12	14.98	10.63

(iii) Corporate Bond Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	10.89	10.40	2.18	4.09	1.96	3.91	−24.47	−5.28
2	22.71	11.20	2.53	4.68	0.72	1.89	−29.37	−10.60
3	33.05	13.36	2.36	4.30	0.29	3.66	−24.13	−9.85
4	40.24	21.21	2.41	4.28	0.96	3.73	−25.29	−10.66
5	43.25	25.13	2.29	3.84	1.04	6.02	−24.60	−7.29
6	46.62	28.66	2.11	4.15	1.22	6.62	−23.93	−5.79
7*	57.96	31.43	2.09	4.21	1.31	13.81	−15.62	1.93
8	60.52	32.06	2.18	4.77	1.39	17.06	−12.51	6.70
9	62.29	33.43	2.10	4.58	1.12	19.00	−10.90	8.87
10	64.66	33.60	2.17	5.64	1.37	18.07	−12.71	7.81

(iv) Option Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	16.76	6.17	28.61	5.45	11.38	29.56	9.25	13.73
2*	33.23	8.40	28.59	8.50	11.35	29.95	11.35	14.80
3	36.08	10.24	28.56	8.81	11.29	30.09	14.41	15.21
4	47.37	11.92	28.58	7.31	11.32	30.25	15.46	15.51
5	58.15	15.68	28.58	7.10	11.34	30.49	15.38	15.73
6	60.15	16.78	28.55	7.11	11.26	30.59	15.72	15.81
7	61.98	16.86	28.53	7.50	11.19	30.65	16.09	15.99
8	67.76	18.07	28.53	9.09	11.21	30.73	16.17	16.14
9	68.79	18.56	28.53	9.37	11.21	30.80	16.27	16.33
10	69.98	18.77	28.53	9.31	11.23	30.95	16.49	16.56

This table reports the in-sample and out-of-sample performance of the restricted common factor model in (7.2). Panels report R^2's for (i) all returns, (ii) stocks, (iii) corporate bonds, and (iv) options. K is the number of factors; * marks the estimator of K that maximizes the ratio of adjacent eigenvalues. R^2_K captures the variation explained in characteristic-managed portfolios by PCA factors. $R^2_{\bar{R}}$ is the R^2 from the Fama–MacBeth cross-sectional regression. R^2 is the total in-sample R^2 defined in (2.9). R^2_O, $R^2_{T,N,O}$, and $R^2_{N,T,O}$ measure out-of-sample predictability, see (2.10) - (2.12). $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit based on factors approximated by (2.13), see (2.14)–(2.16). All R^2's are reported in percentage terms.

Table A6: Out-of-sample fit of the unrestricted common factor model using factor approximation (5.1)

(i) All the returns on three asset classes

K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	24.62	0.22	9.78
2	24.97	4.09	10.46
3	25.41	6.18	11.37
4	25.30	5.45	11.25
5	25.36	3.59	11.43
6	25.83	5.30	12.13
7	25.96	7.54	12.56
8	25.89	7.83	12.52
9	25.93	7.51	12.61
10	26.07	7.61	12.77

(ii) Stock Returns

K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	3.99	4.63	3.12
2	4.17	4.84	3.23
3	5.01	6.41	3.98
4	4.85	5.76	3.88
5	5.68	6.96	4.71
6	6.49	8.04	5.55
7	5.35	5.41	4.55
8	5.28	5.36	4.41
9	5.18	5.25	3.86
10	5.91	6.10	4.54

(iii) Corporate Bond Returns

K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	5.65	−15.01	−0.75
2	10.51	−13.02	2.41
3	12.71	−11.04	5.51
4	12.71	−14.70	2.58
5	11.60	−18.40	0.97
6	12.07	−19.74	0.93
7	14.83	−16.83	4.68
8	15.15	−17.73	3.50
9	17.71	−14.30	6.05
10	18.51	−12.89	6.01

(iv) Option Returns

K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	28.60	0.35	11.08
2	28.88	4.32	11.86
3	29.23	6.43	12.70
4	29.12	5.73	12.45
5	29.07	3.84	12.32
6	29.48	5.60	13.01
7	29.79	7.94	13.56
8	29.71	8.26	13.57
9	29.73	7.88	13.66
10	29.74	7.95	13.69

This table reports out-of-sample performance of the common factor model in (2.7), based on out-of-sample factors approximated by (5.1). Panels report R^2's for (i) all returns, (ii) stocks, (iii) corporate bonds, and (iv) options. K is the number of factors; $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit, see (2.14)–(2.16). All R^2's are reported in percentage terms.

Table A7: In-sample and out-of-sample performance of the factor models for each asset class

(i) Stock Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	28.63	3.10	8.57	7.86	7.46
2	43.55	3.27	9.32	9.11	8.16
3	53.93	4.22	12.17	15.04	10.79
4	61.52	5.85	12.54	15.60	11.10
5	67.93	11.46	13.04	16.18	11.61
6	73.19	14.38	13.48	16.58	12.03
7	77.04	14.68	13.70	16.85	12.24
8	80.63	14.95	13.84	16.83	12.38
9	83.84	15.20	14.12	17.09	12.68
10	86.29	15.49	14.22	17.00	12.78
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.22	0.71	0.04	18.64	

(ii) Corporate Bond Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	27.85	8.09	8.68	−9.67	4.91
2	44.54	16.37	25.28	5.03	19.75
3*	59.16	30.76	29.40	11.77	23.08
4	66.93	34.84	30.50	11.05	23.95
5	73.39	37.24	33.54	17.13	27.35
6	78.23	39.47	34.26	17.70	28.15
7	81.61	40.12	35.18	18.59	29.21
8	84.54	40.90	37.40	19.36	31.92
9	87.21	42.25	37.76	20.02	32.29
10	89.29	42.97	38.16	20.69	32.79
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	2.22	5.48	1.67	47.68	

(iii) Option Returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	32.16	7.04	−443.77	45.56	−448.34
2	52.18	9.33	−440.09	47.81	−445.63
3	62.41	18.11	−435.84	47.87	−441.94
4	70.07	22.22	−434.60	47.11	−440.66
5	77.06	22.75	−432.62	46.67	−438.92
6	81.53	23.28	−431.36	46.55	−437.83
7	84.66	23.58	−430.62	46.45	−437.09
8	87.61	23.89	−429.77	46.26	−436.21
9	89.79	24.15	−428.69	46.06	−435.04
10	91.91	24.46	−426.85	46.05	−433.16
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	−453.05	46.21	−454.85	27.80	

This table reports the in-sample and out-of-sample performance of the factor model in (2.4) for each asset class separately. Panels report R^2's for (i) stocks, (ii) corporate bonds, and (iii) options. K is the number of factors; * marks the estimator of K that maximizes the ratio of adjacent eigenvalues. R^2_K captures the variation explained in characteristic-managed portfolios by PCA factors. $R^2_{\tilde{R}}$ is the R^2 from the Fama–MacBeth cross-sectional regression. R^2 is the total in-sample R^2 defined in (2.9). R^2_O, $R^2_{T,N,O}$, and $R^2_{N,T,O}$ measure out-of-sample predictability, see (2.10) - (2.12). $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit based on factors approximated by (2.13), see (2.14)–(2.16). All R^2's are reported in percentage terms.

Table A8: In-sample and out-of-sample performance of the restricted factor models for each asset class

(i) Stock Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	28.65	2.91	0.35	0.71	0.04	8.68	8.41	7.56
2	43.57	3.08	0.34	0.69	0.03	9.40	9.49	8.23
3	53.95	4.02	0.29	0.73	−0.07	12.13	15.30	10.76
4	61.54	5.52	0.27	0.77	−0.06	12.56	15.88	11.13
5	67.96	11.32	0.11	0.22	−0.05	13.07	16.40	11.66
6	73.21	14.22	0.18	0.66	−0.05	13.51	16.83	12.05
7	77.07	14.52	0.18	0.59	−0.04	13.73	17.04	12.26
8	80.67	14.74	0.18	0.53	−0.04	13.86	17.18	12.41
9	83.88	15.04	0.15	0.43	−0.06	14.16	17.32	12.72
10	86.33	15.34	0.10	0.30	−0.11	14.26	17.38	12.82

(ii) Corporate Bond Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	27.85	6.40	0.29	1.66	0.43	9.47	−8.20	6.29
2	44.57	17.20	2.19	6.38	2.87	26.48	8.44	21.60
3*	59.18	30.76	1.91	6.07	2.39	30.56	14.15	25.21
4	66.96	34.97	1.76	5.72	2.17	31.54	14.85	25.99
5	73.41	37.22	2.17	7.12	2.49	33.99	19.07	28.25
6	78.26	39.33	2.20	6.25	2.26	34.58	19.25	28.90
7	81.65	40.06	2.04	5.88	2.13	35.76	20.40	30.08
8	84.57	40.82	2.10	4.85	1.78	37.69	21.15	32.44
9	87.24	42.18	2.04	4.96	1.71	38.01	20.99	32.75
10	89.32	42.90	1.98	4.79	1.49	38.36	21.35	33.19

(iii) Option Returns

K	R^2_K	R^2	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1*	35.08	7.61	−453.35	46.37	−455.06	−442.25	46.44	−446.96
2	53.90	8.21	−454.20	47.31	−455.85	−439.93	46.95	−445.04
3	64.11	16.51	−453.87	47.05	−455.40	−435.79	46.71	−441.50
4	71.58	21.44	−453.31	46.34	−455.12	−434.31	46.51	−440.22
5	77.89	22.59	−453.21	46.24	−455.06	−432.62	46.62	−438.78
6	82.32	23.13	−453.21	46.27	−455.01	−431.52	46.50	−437.69
7	85.45	23.38	−453.14	46.18	−454.98	−430.79	46.52	−437.05
8	88.22	23.86	−453.09	46.10	−454.94	−430.01	46.40	−436.27
9	90.35	24.06	−453.05	46.14	−454.90	−428.59	46.33	−434.68
10	92.20	24.52	−453.09	46.26	−454.89	−427.00	46.21	−433.15

This table reports the in-sample and out-of-sample performance of the factor model in (7.1) for each asset class separately. Panels report R^2's for (i) stocks, (ii) corporate bonds, and (iii) options. K is the number of factors; * marks the estimator of K that maximizes the ratio of adjacent eigenvalues. R^2_K captures the variation explained in characteristic-managed portfolios by PCA factors. $R^2_{\bar{R}}$ is the R^2 from the Fama–MacBeth cross-sectional regression. R^2 is the total in-sample R^2 defined in (2.9). R^2_O, $R^2_{T,N,O}$, and $R^2_{N,T,O}$ measure out-of-sample predictability, see (2.10) - (2.12). $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit based on factors approximated by (2.13), see (2.14)–(2.16). All R^2's are reported in percentage terms.

Table A9: Out-of-sample performance of the pure-alpha strategy based on the factor models for each asset class

(i) Stock Returns

K	μ_α	σ_α	SR_α
1	0.26	0.51	0.51
2	0.33	0.44	0.73
3	0.34	0.45	0.75
4	0.39	0.45	0.87
5	0.36	0.44	0.82
6	0.29	0.32	0.91
7	0.29	0.29	0.99
8	0.29	0.27	1.07
9	0.32	0.27	1.19
10	0.34	0.26	1.34

(ii) Corporate Bond Returns

K	μ_α	σ_α	SR_α
1	0.06	0.05	1.09
2	0.02	0.04	0.56
3	0.03	0.04	0.76
4	0.03	0.03	1.06
5	0.01	0.02	0.50
6	0.01	0.02	0.39
7	0.01	0.02	0.62
8	0.01	0.02	0.60
9	0.01	0.02	0.89
10	0.01	0.01	0.75

(iii) Option Returns

K	μ_α	σ_α	SR_α
1	0.08	0.42	0.19
2	0.21	0.33	0.65
3	0.37	0.18	2.06
4	0.28	0.15	1.83
5	0.27	0.14	1.94
6	0.22	0.11	2.04
7	0.17	0.10	1.73
8	0.14	0.10	1.47
9	0.15	0.08	1.77
10	0.08	0.06	1.36

This table reports the out-of-sample performance of pure-alpha strategy in (2.17) based on the factor models in (2.4) for each asset class. K denotes the number of factors specified. μ_α, σ_α and SR_α are the annualized means (%), standard deviations (%), and Sharpe ratios of the pure-alpha strategy.

Table A10: Out-of-sample R^2s and performance of the pure-alpha strategy for the extended sample period ending December 2021

(i) All the returns on three asset classes

	Case (1)						Case (2)					
K	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	9.99	5.35	1.87	36.12	8.33	15.18	11.96	3.26	3.66	10.57	8.92	7.21
2	4.97	4.86	1.02	36.52	11.49	16.37	7.86	2.98	2.64	13.22	12.66	9.30
3	4.67	4.23	1.10	36.87	14.95	17.08	7.41	2.62	2.82	15.27	16.70	10.61
4	3.51	3.80	0.93	37.04	14.85	17.37	6.82	2.57	2.66	16.42	16.90	11.09
5	3.41	3.76	0.91	37.19	14.73	17.64	6.75	2.53	2.67	16.95	16.84	11.52
6	4.04	3.72	1.09	37.33	14.39	18.02	6.64	2.50	2.65	17.81	16.57	12.13
7	5.01	3.74	1.34	37.37	13.36	18.19	6.96	2.45	2.84	18.12	15.64	12.37
8	4.39	3.16	1.39	38.08	15.19	18.51	5.95	2.20	2.70	18.53	17.62	12.81
9	3.85	2.89	1.33	38.16	15.81	18.77	5.46	1.93	2.82	19.04	18.41	13.25
10	3.74	3.01	1.24	38.80	15.91	18.97	4.98	1.63	3.05	19.30	18.62	13.46
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$				R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$			
1-10	34.95	7.70	11.52				2.14	7.95	1.95			

(ii) Stock Returns

	Case (1)						Case (2)					
K	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	0.26	0.70	0.37	−0.87	0.43	5.67	0.26	0.70	0.37	7.52	9.68	6.92
2	0.25	0.73	0.34	4.35	7.72	7.32	0.25	0.73	0.34	9.48	12.10	8.05
3	0.33	0.65	0.51	8.46	11.29	8.78	0.33	0.65	0.51	11.09	13.95	9.22
4	0.32	0.69	0.47	7.57	10.38	8.78	0.32	0.69	0.47	11.19	13.96	9.41
5	0.29	0.67	0.44	6.46	9.41	8.73	0.29	0.67	0.44	11.45	14.16	9.74
6	0.28	0.69	0.40	8.26	10.67	9.04	0.28	0.69	0.40	11.78	14.39	9.93
7	0.31	0.60	0.52	8.51	10.86	9.30	0.31	0.60	0.52	12.03	14.65	10.23
8	0.26	0.74	0.35	5.06	6.39	9.03	0.26	0.74	0.35	12.21	14.62	10.37
9	0.26	0.75	0.35	5.92	7.47	9.36	0.26	0.75	0.35	12.50	14.78	10.59
10	0.30	0.65	0.46	3.41	5.13	9.17	0.30	0.65	0.46	12.73	15.18	10.72
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$				R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$			
1-10	0.33	0.63	0.07				0.33	0.63	0.07			

(iii) Corporate Bond Returns

	Case (1)						Case (2)					
K	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	0.66	0.74	0.89	−7.12	−30.06	−44.87	0.66	0.74	0.89	5.98	−28.00	−18.26
2	−0.31	0.91	−0.34	−29.77	−43.49	−94.54	−0.31	0.91	−0.34	0.04	−34.28	−36.03
3	−0.36	0.97	−0.37	−2.16	−33.92	−37.86	−0.36	0.97	−0.37	9.64	−25.75	−14.77
4	−0.26	1.00	−0.26	2.13	−31.06	−30.46	−0.26	1.00	−0.26	11.32	−23.27	−12.85
5	−0.26	0.99	−0.26	−0.42	−30.87	−36.10	−0.26	0.99	−0.26	12.95	−22.77	−10.23
6	−0.40	1.03	−0.39	1.93	−23.60	−39.81	−0.40	1.03	−0.39	19.90	−15.15	−3.08
7	−0.17	1.06	−0.16	2.03	−21.61	−41.51	−0.17	1.06	−0.16	22.43	−11.47	0.03
8	−0.09	0.88	−0.11	−46.29	−24.00	−146.59	−0.09	0.88	−0.11	24.12	−10.17	2.12
9	−0.08	0.73	−0.10	−57.23	−22.13	−171.81	−0.08	0.73	−0.10	26.93	−7.35	6.32
10	−0.04	0.66	−0.05	−57.79	−23.08	−176.25	−0.04	0.66	−0.05	28.89	−5.95	7.70
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$				R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$			
1-10	1.60	2.10	0.44				1.60	2.10	0.44			

(iv) Option Returns

	Case (1)						Case (2)					
K	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$	μ_α	σ_α	SR_α	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	9.06	5.16	1.76	37.64	8.83	15.88	11.03	3.09	3.57	13.24	9.30	6.47
2	5.03	4.45	1.13	37.97	12.05	17.51	7.92	2.48	3.19	17.19	13.14	10.23
3	4.69	4.01	1.17	38.07	15.51	18.04	7.43	2.21	3.37	18.87	17.21	11.49
4	3.45	3.45	1.00	38.26	15.40	18.30	6.76	2.03	3.33	20.74	17.38	12.02
5	3.37	3.42	0.98	38.46	15.27	18.49	6.71	2.01	3.33	21.38	17.31	12.32
6	4.16	3.33	1.25	38.54	14.84	18.64	6.77	1.91	3.53	22.08	16.96	12.54
7	4.87	3.48	1.40	38.56	13.76	18.67	6.82	1.90	3.59	22.22	15.96	12.43
8	4.23	2.79	1.52	39.64	15.72	19.07	5.78	1.69	3.42	22.70	17.99	13.18
9	3.67	2.56	1.43	39.74	16.32	19.26	5.27	1.50	3.52	23.16	18.77	13.58
10	3.47	2.85	1.22	40.50	16.47	19.48	4.72	1.36	3.47	23.29	18.96	13.81
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$				R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$			
1-10	36.34	7.89	13.75				3.52	8.14	3.98			

This table reports the out-of-sample performance of the factor model in (2.7), with the out-of-sample period extended to December 2021. Panels report R^2's for (i) all returns, (ii) stocks, (iii) corporate bonds, and (iv) options. Case (1) uses non-trimmed options data and Case (2) uses trimmed options data for out-of-sample evaluation. K is the number of factors. R^2_O, $R^2_{T,N,O}$, and $R^2_{N,T,O}$ measure out-of-sample predictability, see (2.10) - (2.12). $R^2_{f,O}$, $R^2_{f,T,N,O}$, and $R^2_{f,N,T,O}$ assess out-of-sample fit based on factors approximated by (2.13), see (2.14)–(2.16). All R^2's are reported in percentage terms. μ_α, σ_α and SR_α are the annualized means (%), standard deviations (%), and Sharpe ratios of the pure-alpha strategy.

Table A11: In-sample Sharpe ratios and correlations of MVE portfolios with the covariance matrix approximated by factors using the restricted factor models

(i) Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE and its constituents	2.03	2.10	1.00	0.37
Asset-class MVE	-	2.78	1.36	2.61
(ii) Correlations between constituents in joint MVE				
	Joint	Stock	CorpBond	Option
Joint	-	0.24***	0.19***	0.73***
Stock	-	-	-0.06	-0.22***
CorpBond	-	-	-	-0.35***
(iii) Correlations between constituents in joint MVE and common factors				
	Joint	Stock	CorpBond	Option
Common 1	-0.10	-0.30***	0.34***	-0.14**
Common 2	-0.07	0.00	-0.05	-0.04
Common 3	-0.11	0.14**	0.06	-0.21***
Common 4	-0.03	0.11*	0.34***	-0.28***
Common 5	-0.09	-0.01	-0.29***	0.07
Common 6	-0.04	0.08	0.20***	-0.19***
Common 7	0.00	0.00	-0.07	0.04
Common 8	-0.09	0.09	0.07	-0.17**
Common 9	0.00	0.13*	-0.14**	0.02
Common 10	-0.01	-0.04	0.01	0.00

This table reports the in-sample performance of MVE portfolios constructed from the first ten estimated regressed-PCA factors using the restricted common factor model in (7.2) and the restricted factor model in (7.1) for each asset class separately. Panel (i) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class MVE portfolios. Panel (ii) reports correlations among the constituents of the joint MVE portfolio. Panel (iii) reports correlations between the constituents of the joint MVE portfolio and the common factors. We approximate the covariance matrix of characteristic-managed portfolios using (6.4).

Table A12: Out-of-sample Sharpe ratios of MVE portfolios

Number of factors	Joint	Stock	CorpBond	Option
$K = 1$	1.49	-0.10	0.94	1.21
	-	[1.47]	[0.87]	[1.04]
$K = 2$	1.81	0.92	-0.94	1.50
	-	[1.51]	[0.67]	[1.43]
$K = 3$	1.80	0.52	-1.06	1.83
	-	[2.00]	[0.77]	[1.59]
$K = 4$	1.84	0.65	-1.19	1.88
	-	[2.08]	[0.79]	[1.62]
$K = 5$	2.03	0.89	-1.25	1.97
	-	[2.04]	[0.60]	[1.77]
$K = 6$	1.95	0.96	-1.37	1.94
	-	[2.32]	[0.56]	[1.82]
$K = 7$	2.05	1.18	-1.36	1.99
	-	[2.39]	[0.88]	[1.65]
$K = 8$	2.24	1.16	-1.15	2.02
	-	[2.34]	[1.26]	[1.68]
$K = 9$	2.37	1.51	-0.86	1.95
	-	[2.51]	[1.55]	[1.59]
$K = 10$	2.49	1.43	-0.70	2.02
	-	[2.52]	[1.53]	[1.50]
$K = 11$	2.54	1.41	-0.48	2.00
	-	[2.54]	[1.42]	[1.67]
$K = 12$	2.73	1.43	-0.01	2.06
	-	[2.46]	[1.38]	[1.60]
$K = 13$	2.88	1.39	0.66	2.07
	-	[2.29]	[1.37]	[1.63]
$K = 14$	2.94	1.36	1.14	2.02
	-	[2.38]	[1.35]	[1.50]
$K = 15$	2.88	1.30	1.05	2.00
	-	[2.43]	[1.31]	[1.40]
$K = 16$	2.78	1.18	1.03	1.99
	-	[2.49]	[0.97]	[1.51]
$K = 17$	2.79	1.32	1.02	1.98
	-	[2.49]	[0.48]	[1.42]
$K = 18$	2.83	1.61	0.80	1.98
	-	[2.56]	[0.69]	[1.41]
$K = 19$	2.69	1.79	0.99	1.78
	-	[2.54]	[0.73]	[2.32]
$K = 20$	2.81	1.95	1.10	1.86
	-	[2.58]	[0.85]	[2.36]

This table reports the out-of-sample Sharpe ratios (annualized) performance of MVE portfolios constructed from the first twenty estimated regressed-PCA factors of the common factor model in (2.7) and the factor model in (2.4) for each asset class separately. For each number of factors K, the first row gives the Sharpe ratios of the joint MVE portfolio and its constituents in each asset class; the second row reports the Sharpe ratios of the MVE portfolios within each asset class in square brackets.

Table A13: Out-of-sample Sharpe ratios of MVE portfolios for the extended sample period ending December 2021

Number of factors	Joint	Stock	CorpBond	Option
$K = 1$	1.15	-0.17	0.88	1.06
	-	[1.43]	[0.56]	[1.12]
$K = 2$	1.26	0.58	-0.82	1.29
	-	[1.48]	[0.44]	[1.55]
$K = 3$	1.82	0.48	-0.85	1.86
	-	[1.97]	[0.60]	[1.65]
$K = 4$	1.98	0.47	-0.88	2.00
	-	[1.97]	[0.64]	[1.53]
$K = 5$	2.14	0.59	-0.91	2.11
	-	[1.90]	[0.46]	[1.24]
$K = 6$	2.15	0.70	-1.09	2.20
	-	[2.17]	[0.47]	[1.39]
$K = 7$	2.18	0.92	-1.09	2.21
	-	[2.26]	[0.73]	[0.93]
$K = 8$	1.89	0.86	-0.92	1.91
	-	[2.22]	[0.95]	[0.87]
$K = 9$	1.99	1.05	-0.61	1.90
	-	[2.37]	[1.29]	[0.89]
$K = 10$	1.36	0.96	-0.51	1.25
	-	[2.38]	[1.22]	[1.56]
$K = 11$	1.98	1.14	-0.30	1.75
	-	[2.39]	[1.05]	[1.59]
$K = 12$	2.14	1.24	0.15	1.73
	-	[2.36]	[1.05]	[1.64]
$K = 13$	2.36	1.21	0.73	1.85
	-	[2.23]	[1.03]	[1.39]
$K = 14$	2.37	1.18	1.14	1.76
	-	[2.26]	[0.97]	[0.94]
$K = 15$	2.30	1.09	0.95	1.76
	-	[2.30]	[0.87]	[1.28]
$K = 16$	2.35	1.02	0.93	1.82
	-	[2.35]	[0.60]	[1.36]
$K = 17$	2.33	1.15	0.96	1.79
	-	[2.34]	[0.05]	[1.18]
$K = 18$	2.37	1.39	0.79	1.76
	-	[2.39]	[0.18]	[0.98]
$K = 19$	2.28	1.55	0.93	1.61
	-	[2.38]	[0.17]	[1.41]
$K = 20$	2.15	1.83	1.09	1.42
	-	[2.43]	[0.28]	[1.48]

This table reports the out-of-sample Sharpe ratios (annualized) performance of MVE portfolios constructed from the first twenty estimated regressed-PCA factors of the common factor model in (2.7) and the factor model in (2.4) for each asset class separately. For each number of factors K, the first row gives the Sharpe ratios of the joint MVE portfolio and its constituents in each asset class; the second row reports the Sharpe ratios of the MVE portfolios within each asset class in square brackets. The sample period extends to December 2021.

Table A14: Out-of-sample Sharpe ratios of MVE portfolios using the restricted factor models

Number of factors	Joint	Stock	CorpBond	Option
$K = 1$	1.20	-0.22	0.64	1.26
	-	[1.44]	[0.87]	[0.81]
$K = 2$	1.53	1.06	-1.21	1.49
	-	[1.48]	[0.66]	[0.82]
$K = 3$	1.37	0.84	-1.36	1.58
	-	[1.87]	[0.75]	[1.32]
$K = 4$	1.37	0.79	-1.25	1.57
	-	[1.99]	[0.84]	[1.26]
$K = 5$	1.67	1.22	-1.25	1.61
	-	[1.91]	[0.57]	[1.33]
$K = 6$	1.43	1.53	-1.43	1.38
	-	[2.24]	[0.55]	[1.48]
$K = 7$	1.82	1.67	-0.45	1.43
	-	[2.22]	[0.91]	[1.33]
$K = 8$	1.96	1.71	1.15	1.20
	-	[2.14]	[1.19]	[1.33]
$K = 9$	1.87	1.70	1.08	1.09
	-	[2.32]	[1.48]	[1.42]
$K = 10$	2.07	1.26	0.89	1.38
	-	[2.25]	[1.39]	[1.47]
$K = 11$	1.86	0.93	1.47	1.31
	-	[2.40]	[1.30]	[1.63]
$K = 12$	1.92	0.84	1.48	1.35
	-	[2.23]	[1.21]	[1.53]
$K = 13$	1.92	0.76	1.33	1.24
	-	[2.12]	[1.20]	[1.60]
$K = 14$	1.85	0.85	1.16	1.15
	-	[2.38]	[1.04]	[1.77]
$K = 15$	1.94	0.93	1.10	1.25
	-	[2.36]	[0.91]	[1.75]
$K = 16$	1.91	1.06	1.07	1.25
	-	[2.37]	[0.54]	[1.88]
$K = 17$	2.07	1.60	0.93	1.23
	-	[2.21]	[0.43]	[1.80]
$K = 18$	2.25	1.94	0.68	1.34
	-	[2.47]	[0.66]	[2.31]
$K = 19$	2.31	2.10	0.99	1.31
	-	[2.65]	[0.69]	[2.37]
$K = 20$	2.30	2.05	1.19	1.27
	-	[2.68]	[0.87]	[2.36]

This table reports the out-of-sample Sharpe ratios (annualized) performance of MVE portfolios constructed from the first twenty estimated regressed-PCA factors of the restricted common factor model in (7.2) and the restricted factor model in (7.1) for each asset class separately. For each number of factors K, the first row gives the Sharpe ratios of the joint MVE portfolio and its constituents in each asset class; the second row reports the Sharpe ratios of the MVE portfolios within each asset class in square brackets.

Table A15: Correlations of out-of-sample MVE portfolios

(i) Correlations between constituents in joint MVE

	Joint	Stock	CorpBond	Option
Joint	-	0.28***	-0.00	0.91***
Stock	-	-	-0.18**	-0.12
CorpBond	-	-	-	-0.09

(ii) Correlations between constituents in joint MVE and common factors

	Joint	Stock	CorpBond	Option
Common 1	-0.05	-0.23***	0.25***	0.01
Common 2	0.12	-0.19**	0.19**	0.18**
Common 3	0.06	0.04	0.08	0.03
Common 4	0.36***	0.13	-0.09	0.33***
Common 5	0.15*	0.17*	-0.13	0.10
Common 6	-0.21**	0.15*	-0.07	-0.27***
Common 7	-0.27***	-0.16*	-0.05	-0.20**
Common 8	-0.13	0.06	0.18**	-0.19**
Common 9	-0.22**	0.17*	-0.17*	-0.27***
Common 10	-0.20**	0.07	-0.18**	-0.20**
Common 11	-0.17*	0.09	0.03	-0.22**
Common 12	-0.07	0.20**	-0.17*	-0.14
Common 13	0.15*	0.08	-0.18**	0.15*
Common 14	-0.28***	-0.02	-0.09	-0.26***
Common 15	0.03	-0.10	0.03	0.07
Common 16	-0.00	-0.07	-0.02	0.03
Common 17	-0.06	-0.02	0.01	-0.06
Common 18	0.24***	0.04	-0.01	0.23**
Common 19	-0.01	0.02	0.18**	-0.05
Common 20	0.01	-0.15*	0.02	0.07

This table reports the correlations among the constituents of the out-of-sample joint MVE portfolios (Panel (i)), and correlations between the constituents of the out-of-sample joint MVE portfolio and the common factors (Panel (ii)). The out-of-sample realized factors are defined in (5.1).

Table A16: Correlations of out-of-sample MVE portfolios for the extended sample period ending December 2021

(i) Correlations between constituents in joint MVE

	Joint	Stock	CorpBond	Option
Joint	-	0.30***	0.05	0.93***
Stock	-	-	-0.10	-0.05
CorpBond	-	-	-	-0.05

(ii) Correlations between constituents in joint MVE and common factors

	Joint	Stock	CorpBond	Option
Common 1	0.15*	-0.07	0.21**	0.15*
Common 2	-0.07	-0.10	0.14*	-0.05
Common 3	0.33***	-0.02	0.06	0.34***
Common 4	0.04	-0.02	-0.13	0.07
Common 5	-0.04	-0.01	-0.14*	-0.02
Common 6	0.24***	0.09	0.03	0.21***
Common 7	0.18**	-0.06	0.01	0.21**
Common 8	-0.53***	-0.02	0.06	-0.55***
Common 9	-0.36***	0.08	-0.11	-0.39***
Common 10	-0.48***	-0.01	-0.09	-0.49***
Common 11	0.37***	0.03	0.04	0.37***
Common 12	-0.51***	0.03	-0.11	-0.53***
Common 13	-0.39***	0.01	-0.13	-0.40***
Common 14	-0.27***	-0.02	-0.08	-0.26***
Common 15	0.52***	0.00	0.02	0.54***
Common 16	0.55***	0.03	0.06	0.56***
Common 17	0.33***	0.01	0.03	0.34***
Common 18	0.58***	0.06	0.03	0.58***
Common 19	0.48***	0.05	0.15*	0.46***
Common 20	-0.44***	-0.07	-0.01	-0.43***

This table reports the correlations among the constituents of the out-of-sample joint MVE portfolios (Panel (i)), and correlations between the constituents of the out-of-sample joint MVE portfolio and the common factors (Panel (ii)). The out-of-sample realized factors are defined in (5.1). The sample period extends to December 2021.

Table A17: Correlations of out-of-sample MVE portfolios using the restricted factor models

(i) Correlations between constituents in joint MVE

	Joint	Stock	CorpBond	Option
Joint	-	0.41***	-0.01	0.88***
Stock	-	-	-0.02	-0.03
CorpBond	-	-	-	-0.19**

(ii) Correlations between constituents in joint MVE and common factors

	Joint	Stock	CorpBond	Option
Common 1	0.02	-0.15*	0.36***	0.02
Common 2	-0.04	-0.04	0.06	-0.03
Common 3	-0.04	0.10	0.04	-0.10
Common 4	0.29***	0.22**	-0.18**	0.24***
Common 5	0.04	0.15*	-0.19**	0.01
Common 6	-0.42***	-0.06	-0.06	-0.41***
Common 7	-0.04	-0.08	0.16*	-0.03
Common 8	0.12	0.30***	0.07	-0.03
Common 9	-0.09	0.17*	-0.26***	-0.13
Common 10	-0.10	0.02	-0.16*	-0.09
Common 11	-0.15*	0.02	-0.12	-0.15
Common 12	-0.02	0.08	-0.15*	-0.04
Common 13	0.28***	-0.00	-0.18**	0.34***
Common 14	-0.07	-0.07	0.12	-0.07
Common 15	0.24***	-0.08	0.09	0.28***
Common 16	0.06	-0.02	-0.08	0.09
Common 17	0.14	0.06	0.08	0.11
Common 18	0.24***	0.04	-0.02	0.25***
Common 19	-0.07	-0.04	0.15*	-0.09
Common 20	-0.00	-0.17*	-0.05	0.09

This table reports the correlations among the constituents of the out-of-sample joint MVE portfolios (Panel (i)), and correlations between the constituents of the out-of-sample joint MVE portfolio and the common factors (Panel (ii)). The MVE portfolios are constructed from the restricted factor models (7.1) and (7.2). The out-of-sample realized factors are defined in (5.1).