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

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Abstract

We identify a strong common risk factor structure that is pervasive across corporate securities: stocks, corporate bonds, and options. The common factors are related to key economic indicators, and display some out-of-sample forecasting ability. These factors explain substantial variation in individual asset returns, although pricing errors persist. A joint mean-variance efficient portfolio across asset classes achieves a high Sharpe ratio, resulting in part from cross-market hedging of the common factors. We develop a measure of market integration based on the differences in common factor risk premia between markets and document a significant degree of segmentation.

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1 Introduction

Finance theory predicts a tight connection between the major types of corporate securities, such as stocks, corporate bonds, and options (Black and Scholes, 1973; Merton, 1974). Existence of a pervasive factor structure also suggests that cross-sectional variation in expected returns should reflect the different exposures of individual assets to these factors, since common risks cannot be diversified away (Ross, 1976). Yet empirical challenges have impeded efforts to identify common factors across different markets. For instance, available datasets covering asset classes with short maturities, such as corporate bonds and options, have far more securities than time-series observations, making estimation of factors via principal components infeasible. Popular portfolio-sorting approaches to constructing factors, e.g. as in Fama and French (1992), also struggle in the face of a large set of characteristics that are known to forecast returns within each asset class (Cochrane, 2011).[1]

In this paper, we develop a new approach to extract latent factors directly from the large cross-sectional individual securities of the three asset markets based on the regressed-PCA method in Chen, Roussanov, and Wang (2021). The key advantage of this approach is that it works effectively on large panels of assets with large cross-sections but short time series of individual asset returns. Regressed-PCA builds on the classical Fama–MacBeth cross-sectional regressions (Fama and MacBeth, 1973) and principal component analysis (PCA) in a semiparametric conditional factor model, where the time-varying factor loadings and pricing errors of individual asset returns are modeled as flexible functions of observable characteristics. Essentially, regressed-PCA transforms a high-dimensional, unbalanced panel of individual assets into a smaller balanced panel of characteristic-managed portfolios and then applies standard PCA methods to these portfolios to uncover the latent factors. Chen, Roussanov, and Wang (2021) show that the regressed-PCA estimators have desirable large-N asymptotic properties despite short time-series, making it well suited for identifying the common factor structure across multiple asset classes.

[1] Early studies, such as Fama and French (1993), find that stocks and bonds share some common variation, but argue that the underlying risk premia are distinct to each market. Similar market-specific approaches are pursued by Coval and Shumway (2001) for option returns and Lustig, Roussanov, and Verdelhan (2011) for currency returns.

Our empirical analysis is based on monthly observations from June 2004 to December 2021, with 35 characteristics for stocks, 26 for corporate bonds, and 19 for options, including both firm-level and security-specific attributes. Our estimates reveal a strong and systematic common factor structure across the three corporate asset classes. First, common factors are closely related to well-established observable risk factors in the stock, corporate bond, and option markets, but cannot be fully explained by these observed factors. Second, common factorssignificantly load on all asset classes rather than being tied to any single market. This is also confirmed by an analysis based on the asset-class-specific decomposition. Third, the common factors are highly relevant to key macro-financial variables, exhibiting both strong correlations with and demonstrating predictive power for variables such as economic uncertainty and intermediary capital, monetary policy and credit conditions, inflation and real economic activity.

Common factors show a strong performance in explaining and predicting the cross-sectional variation in asset returns across the three asset classes. First, common factors, as tradable portfolios, carry substantial risk premia, with the leading ten factors achieving the maximal annualized in-sample and out-of-sample Sharpe ratios of 1.28 and 2.51, separately. Meanwhile, the common factor model delivers significant explanatory and predictive power: ten common factors explain around 67% and 16.76% of the in-sample return variation in the pooled managed portfolios and individual assets across markets, respectively; they explain and predict 5.42% and 0.20% of out-of-sample variation in next-period returns, separately. Moreover, the explanatory power of common factors in the three asset classes is comparable, although their out-of-sample fit in options is relatively weak. All of these findings justify the strong common factor structure across markets. However, common factors do not fully span the cross-sectional asset returns, where pricing errors persist. Based on the rejection of zero pricing errors, we construct a pure-*alpha* "arbitrage" portfolio that exploits the predictive power of characteristics while bearing zero exposure to common factors. The pure-*alpha* strategy generates a substantial out-of-sample Sharpe ratio around 2; and its decomposition into asset-class-specific components indicates that the high Sharpe ratio comes primarily from the option component, reflecting the large mispricing in options.

Based on the common factor structure, we further construct the joint mean-variance ef-

ficient (MVE) portfolio for individual assets across markets. Assuming that idiosyncratic errors are homoskedastic in the conditional factor model, MVE portfolio then can be approximated with characteristic-managed portfolios, and further common factors. The joint MVE portfolio delivers both higher in-sample and out-of-sample annualized Sharpe ratios, significantly exceeding those of MVE portfolios in each single market. We analyze this outperformance by decomposing the joint MVE portfolio into three asset-class-specific components. Our findings indicate that it is largely due to bilateral hedging among these components, which is further attributed to their opposite loadings on different common factors. Notably, we find that asset-class-specific components hedge against common factors such that the joint MVE portfolio bears almost zero factor exposures, highlighting its efficiency and superiority.

Finally, we measure the extent of integration (or segmentation) between different asset markets based on common factors. Building on the framework of Chen and Knez (1995), we demonstrate that the degree of market segmentation can be measured by the market distance between two asset classes, which is determined by the difference in risk premia of the common basis payoffs. Common factors extracted jointly from individual assets across markets serve as a natural empirical proxy for the basis of the common payoff space. We further demonstrate that the market distance can be equivalently measured by the price difference of common payoffs assigned by corresponding markets. Our empirical results show significant market segmentation for all market pairs, whereas the option market is largely segmented from the other two markets. These findings highlight the limits to cross-market arbitrage of institutional investors.

Our paper contributes to a voluminous empirical asset pricing literature that studies the cross-section of multiple asset classes. Extensive research has documented predictive linkages between stocks and bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Chordia, Goyal, Nozawa, Subrahmanyam, and Tong, 2017; 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, although the robustness of the conclusion remains elusive (Gospodinov and Robotti, 2021). A closely related work by Bali, Beckmeyer, and Goyal (2023) extends the approach of Instrumented Principal Component Analysis (IPCA) in Kelly, Pruitt, and Su (2019) to estimate a joint factor model for the same three asset classes. Based on the similar conditional factor model, we extract factors via regressed-PCA, explicitly accounting for pricing errors and nonlinearity, along with a rigorous weighted bootstrap testing procedure. We construct both common factors for all markets and pairwise factors for different market pairs, which enrich the related literature.

Our paper adds to the growing asset pricing literature on factor models of corporate bonds and options. These two asset markets are relatively under-studied compared to stock market, though recent work has begun to explore the specific factor structures of these two markets. For corporate bonds, Kelly, Palhares, and Pruitt (2023) apply IPCA to extract five latent factors in bond returns, while others identify several aggregate risks such as liquidity (Lin, Wang, and Wu, 2011), long-run consumption risk (Elkamhi, Jo, and Nozawa, 2022), and institutional constraints (Bali, Subrahmanyam, and Wen, 2021). For options, in addition to the traditional parametric models (Duffie, Pan, and Singleton, 2000), the research on factor-based explanations grows rapidly. Büchner and Kelly (2022) exploit IPCA to study the factor structure of index options; Horenstein, Vasquez, and Xiao (2020) use PCA to extract latent factors from option portfolios. Similarly, Christoffersen, Fournier, and Jacobs (2018) extract factors 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). In this paper, we also extract the factors in each asset class based on regressed-PCA, providing additional sets of corporate bond and option factors to the literature.

We develop a new framework to construct the joint MVE portfolio on individual assets across markets. For multiple asset classes, there are much larger cross-section assets than time series, which are also associated with unbalanced panels. Existing approaches (see Ledoit and Wolf, 2017), which focus on estimation of the high-dimensional covariance matrix,

are not feasible in this context. Based on the conditional factor model, our approach incorporates characteristics and enhances the approximation of the conditional MVE portfolio, and further translates the covariance matrix estimation for a high-dimensional unbalanced panel into the estimation for a low-dimensional set of common factors. Consequently, the construction of a joint MVE portfolio across markets becomes feasible with common factors.

We also propose a formal measure of market segmentation built on the idea of Chen and Knez (1995). We demonstrate that the extent of market segmentation should be reflected by the difference in the risk premia of commonly priced factors, which shares some similar logic with the recent studies (He and Krishnamurthy, 2013; Choi and Kim, 2018; Sandulescu, 2019; Patton and Weller, 2022). We particularly highlight common factors as benchmark basis payoffs, and develop several equivalent testing procedures on market segmentation. Our rigorous quantification of segmentation also supports the findings on the cross-market limits to arbitrage as in Kapadia and Pu (2012), Siriwardane, Sunderam, and Wallen (2025), and Wittwer and Uthemann (2025). Lastly, our empirical findings further provide helpful guidance to related theoretical models, especially casting doubt on the assumption of integrated asset markets.

The rest of the paper is organized as follows. Section 2 introduces the regressed-PCA procedure in a conditional factor model across markets. Section 3 describes the data. Section 4 examines the cross-market commonality captured by factors and their economic relevance. Section 5 presents the in-sample and out-of-sample performance of the common factor model. Section 6 constructs the joint MVE portfolios across markets using common factors. Section 7 measures market segmentation based on common factors. Section 8 concludes.

2 Methodology

In this section, we specify the excess returns of individual assets in stock, corporate bond, and option markets with a conditional factor model. We then extend the regressed-PCA approach developed by Chen, Roussanov, and Wang (2021) to extract common factors from individual corporate securities across three asset classes.

2.1 Model

In each asset market, we consider a canonical conditional factor model as in Kelly, Pruitt, and Su (2019) and Chen, Roussanov, and Wang (2021):[2]

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

where $r_{i,t}$ is the excess return of asset i at time t, $z_{i,t-1} = (1, z_{i,t-1,1}, \ldots, z_{i,t-1,J})'$ is a $(J+1)\times 1$ vector of prespecified asset characteristics (including a constant term and J time-varying characteristics) that is observed at the beginning of time period t, and f_t is a $K \times 1$ vector of latent common factors. Both mispricing errors $\alpha(\cdot)$ and dynamic factor loadings $\beta(\cdot)$ are functions of $z_{i,t-1}$ with unknown functional forms. $\epsilon_{i,t}$ is the idiosyncratic error term.

We primarily focus on the linear approximations of $\alpha(z_{i,t-1})$ and $\beta(z_{i,t-1})$, i.e.,

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

where a is a $(J+1) \times 1$ vector, and B is a $(J+1) \times K$ matrix. $\eta_{\alpha,i,t}$ and $\eta_{\beta,i,t}$ are the approximation errors. Let $R_t = (r_{1,t}, ..., r_{N,t})'$, $Z_{t-1} = (z_{1,t-1}, ..., z_{N,t-1})'$, $H_{\alpha,t-1} = (\eta_{\alpha,1,t-1}, \ldots, \eta_{\alpha,N,t-1})'$, $H_{\beta,t-1} = (\eta_{\beta,1,t-1}, \ldots, \eta_{\beta,N,t-1})'$, and $\varepsilon_t = (\epsilon_{1,t}, ..., \epsilon_{N,t})'$. Denote $\xi_t = H_{\alpha,t-1} + H_{\beta,t-1} f_t + \varepsilon_t$, then (2.1) can be rewritten in a matrix form:

$$R_t = Z_{t-1} a + Z_{t-1} B f_t + \xi_t. \tag{2.3}$$

Next, we impose a common factor structure across the three asset markets based on (2.3). Specifically, the returns on stocks (s), corporate bonds (b) and options (o) at time t are specified as:

$$\begin{aligned} R_t^s &= Z_{t-1}^s a_{cs} + Z_{t-1}^s B_{cs} f_t^C + \xi_t^s, \\ R_t^b &= Z_{t-1}^b a_{cb} + Z_{t-1}^b B_{cb} f_t^C + \xi_t^b, \\ R_t^o &= Z_{t-1}^o a_{co} + Z_{t-1}^o B_{co} f_t^C + \xi_t^o. \end{aligned} \tag{2.4}$$

Importantly, the latent factors (f_t^C) capture the common variation across different asset classes, which is our main focus. We stack (2.4) into

[2] To simplify notation, we omit asset-class-specific subscripts and superscripts here.

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

which corresponds to an augmented version of (2.3), that is,

$$\boldsymbol{R}_t = \boldsymbol{Z}_{t-1}\boldsymbol{a} + \boldsymbol{Z}_{t-1}\boldsymbol{B}f_t^C + \boldsymbol{\xi}_t. \tag{2.5}$$

Similarly, the model in (2.3) can also be extended to study the pairwise factor structure for any two asset markets, where the detailed factor structure is shown in Appendix A5. In addition, we also consider the nonlinear specifications of $\alpha(\cdot)$ and $\beta(\cdot)$ in Appendix B1.

2.2 Regressed-PCA

We estimate the models in (2.3) and (2.5) by adopting the regressed-PCA approach developed in Chen, Roussanov, and Wang (2021). We illustrate this two-step estimation procedure using the baseline specification in (2.3). First, we run the period-by-period cross-sectional regression (Fama and MacBeth, 1973) of R_t on Z_{t-1}, that is,

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

where $\tilde{R}_t = (Z_{t-1}'Z_{t-1})^{-1}Z_{t-1}'R_t$ is a $(J+1)\times 1$ vector of characteristic-managed portfolios with zero cost. Second, we apply the standard PCA to the covariance matrix of managed portfolios,[3] i.e., $\tilde{R}M_T\tilde{R}'/T$, where $\tilde{R} = (\tilde{R}_1, \ldots, \tilde{R}_T)$ and $M_T \equiv I_T - 1_T 1_T'/T$ with 1_T being a $T\times 1$ vector of ones. Following Chen, Roussanov, and Wang (2021), we impose the following identification conditions: $a'B = 0$, $B'B = I_K$, and $F'M_TF/T$ is diagonal with descending entries, where $F = (f_1, \ldots, f_T)'$ with all positive sample means such that unconditional risk premium on each factor is positive. As a result, $\hat{B}$ is given by the eigenvectors corresponding to the first K largest eigenvalues of matrix $\tilde{R}M_T\tilde{R}'/T$, and $\hat{a} = (I_{J+1} - \hat{B}\hat{B}')\sum_{t=1}^T \tilde{R}_t/T$.

[3]This corresponds to the unrestricted model ($\alpha(\cdot) \neq 0$), which is the main focus in the following sections unless otherwise noted.

The resulting estimators of $\alpha(\cdot)$, $\beta(\cdot)$ and F are:[4]

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

where B and F are identified up to a rotation matrix.

The model in (2.5) with common factor structure is estimated using an analogous two-step procedure. The Fama-MacBeth cross-sectional regression ($\boldsymbol{R}_{t+1}$ on $\boldsymbol{Z}_t$) yields tradable characteristic-managed portfolios in different asset markets. Notably, this step is equivalent to running separate cross-sectional regressions within each asset class, enabling us to incorporate both security-specific and firm-level characteristics (like firm's leverage) in different asset classes. We then extract the common factors ($\boldsymbol{F}^C$) by applying PCA to the pooled managed portfolios of all asset classes. The resulting factors are zero-cost tradable portfolios constructed on the managed portfolios with weights $\hat{\boldsymbol{B}}$.

Notably, two properties of the regressed-PCA approach demonstrated by Chen, Roussanov, and Wang (2021) are crucial in our setting. First, the method has large-N asymptotic properties and does not require large T. This is particularly appealing for the analysis with a vast cross-sectional observations but relatively shorter sample periods ($N \gg T$). As shown in Section 3, we observe only 210 monthly periods but more than 5,000 individual assets in each month. Second, regressed-PCA also accommodates unbalanced panels. By performing the period-by-period Fama–MacBeth regressions, the method transforms unbalanced, high-dimensional individual asset returns into a balanced, low-dimensional set of tradable managed portfolios. This property is critical for the options, where individual contracts often have short maturities, while long-maturity contracts are usually illiquid. All of these make a balanced panel of individual options over long horizons infeasible.

Finally, we employ the weighted bootstrap procedure developed in Chen, Roussanov, and Wang (2021) to test $\alpha(\cdot) = 0$ and $\beta(\cdot) = 0$.

[4]Here, the number of factors K is pre-specified. Consistent estimates of K can be obtained by maximizing the ratio of adjacent eigenvalues; see Ahn and Horenstein (2013) and Chen, Roussanov, and Wang (2021).

3 Data

In this section, we describe the data on characteristics and returns of individual stocks, corporate bonds and options.

Accounting for data availability across all asset classes, the in-sample analysis runs from July 2004 to December 2021. The out-of-sample analysis spans the sample from July 2004 to December 2019, using the first 60 months as the initial training window. We exclude the last two years (2020-2021) in the out-of-sample analysis to prevent extraordinary events, such as COVID-19 pandemic and the GameStop, from disproportionately skewing the return predictability, particularly for options. As a robustness check, we extend the out-of-sample analysis until the end of 2021, where the results are reported in Appendix A6.

To limit the influence of outliers, we rescale all characteristics cross-sectionally to the range $[-0.5, +0.5]$ as in Kelly, Pruitt, and Su (2019). Appendix A1 provides more details on characteristic construction and data filters.

3.1 Stocks

The monthly data on stock returns and characteristics are from Freyberger, Neuhierl, and Weber (2020) and Freyberger, Höppner, Neuhierl, and Weber (2022) until December 2021. We choose 35 available characteristics, with more details listed in Appendix A1.

3.2 Corporate Bonds

The monthly corporate bond returns and characteristics are from the dataset in Dickerson, Robotti, and Rossetti (2023), which are sourced from the WRDS bond database and Mergent's FISD. The dataset accounts for market microstructure noise (MMN) by employing the adjustment procedure proposed by Andreani, Palhares, and Richardson (2024), which significantly reduces return volatility for illiquid bonds and also reconciles returns derived from transaction data with those from institutional-grade quote data. We further supplement

this dataset with Mergent's FISD for contract-level details such as coupon rates, convertible terms, and issuer information. The resulting datasets are then merged with firm-level characteristics from Compustat and CRSP.

The monthly individual corporate bond returns are computed using representative price (P), accrued interests (AI), and coupons (cpn) on each end-of-month date. We select month-end prices due to the illiquidity and infrequent trading in corporate bond markets, aiming to balance the trade-off between sample size and the use of potentially stale price data. 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. We compute the accrued interest over the fractional period between the last coupon payment date and the month-end date. The monthly bond return is then calculated as

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

We choose 26 characteristics that are informative for corporate bond returns, as documented by the literature (e.g., Kelly, Palhares, and Pruitt, 2023; Bao, Pan, and Wang, 2011). Among these, there are 12 characteristics related to bond contracts, including bond age (age), coupon (cpn), 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 firm-level characteristics, which are also used in the analysis of stock returns. These are idiosyncratic volatility ($idiovol$), momentum (mom), book leverage (lev), operating leverage (ol), earnings-to-price ratio ($e2p$), tangibility (tan), total debt ($debt$), debt-to-EBITDA ($d2ebitda$), distance-to-default (DD), and five characteristics realted to Fama-French factors ($beta$, $prof$, $mktcap$, $invest$, bm). Appendix A1 presents the sources and detailed description of these characteristics.

3.3 Options

The monthly data on individual equity option returns and characteristics are from OptionMetrics. We obtain the underlying stock information such as returns, prices, share codes, and trading volume from CRSP. Importantly, to avoid recording errors and distortions caused by

extremely illiquid options, we apply standard data filters commonly used in the literature.[5] All filters are applied properly to avoid look-ahead bias, where Appendix A1 provides all the details.

Outliers in the options data can significantly distort the estimation, especially during periods of extreme financial market turmoil. To mitigate this issue, 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, while we retain the untrimmed data in the out-of-sample analysis to avoid look-ahead bias.

We focus on call options, which are more actively traded compared to puts (Zhan, Han, Cao, and Tong, 2022; Christoffersen, Goyenko, Jacobs, and Karoui, 2018). Our analysis is based on delta-hedged holding-period returns. Specifically, on each portfolio formation date, we buy one call option contract and sell Δ shares of the underlying stock, where Δ is from OptionMetrics and is calculated based on the Black–Scholes model. We maintain the position for one month without daily rebalancing to reduce transaction costs and improve practicality. The delta-hedged option return is then defined as

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

We select 19 characteristics that are documented in the literature as useful to explain or predict option returns (see Büchner and Kelly, 2022; Zhan, Han, Cao, and Tong, 2022; Bali, Beckmeyer, Moerke, and Weigert, 2021). Seven of them are related to option contracts: implied volatility (*impl_vol*), option Greeks (*delta*, *gamma*, *theta*, *volga*), embedded leverage (*embed_lev*), and an option illiquidity measure (*optspread*). Twelve of them are firm-level or stock characteristics: stock illiquidity (*bidask*), idiosyncratic volatility (*idiovol*), volatility deviation (*vol_dev*), momentum measures (*strev*, *intmom*, *mom*), book leverage (*lev*), and five characteristics related to Fama-French factors (*beta*, *prof*, *mktcap*, *invest*, *bm*). Appendix A1 provides detailed definitions and references for each characteristic.

[5] 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).

3.4 Summary Statistics and Standardization

Table 1 reports descriptive statistics of individual returns in the three markets. After filtering, we retain 738,518 monthly observations for stocks, 208,652 for corporate bonds, and 759,380 for options. There are at least 5,000 individual observations per month in the three asset classes, enabling us to consistently identify the common factor structure among different markets. Table 1 shows large discrepancies in the standard deviations of returns among the three asset classes. To ensure comparability across markets, we scale individual asset returns by the standard deviation of returns within their respective asset class. The standard deviations are estimated using the initial 60-month window to preclude look-ahead bias.

4 Understanding Common Factors

Estimating the conditional factor model in (2.5) using the regressed-PCA approach yields a set of factors that capture common variations across stock, corporate bond, and option markets. Figure 1 plots the cumulative returns of the first five common factors. Several factors exhibit strong systematic fluctuations during major episodes in financial market, indicating that these factors are able to capture the common sources of aggregate risk. In this section, we examine the cross-market commonality captured by the extracted factors and interpret their underlying economic driving forces.

4.1 Commonality

We investigate the commonality captured by the factors from several aspects. We compare them with the observable factors in each asset class. We relate the common factors to the latent factors extracted from individual asset markets via regressed-PCA, and further analyze the contributions of their constituents from different asset classes.

4.1.1 Relation to Observable Factors

We begin by examining the connection between the common factors and observable factors, which have been widely adopted in the literature and shown to explain substantial cross-sectional return variations within each asset class. For stocks, we follow Fama and French (2015) and Carhart (1997) and choose the market factor ($MKTstock$), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (MOM). For corporate bonds, following Bai, Bali, and Wen (2019) and Dickerson, Mueller, and Robotti (2023), we select 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), option-market factor ($MKToption$), and volatility deviation ($VOLDEV$). More details on the observable factors are provided in Appendix A2.

Table 2 reports the correlations between the common factors and observable factors. We find high correlations between two sets of factors. Most of the extracted factors are significantly related to multiple observable factors across asset classes. For example, the first common factor strongly correlates with fifteen out of eighteen observable factors, and the third factor is significantly correlated with sixteen observable factors. The high correlations indicate that the extracted factors, as established observable factors, effectively capture substantial cross-sectional common variation across different asset classes.

Table 3 shows the time-series regression results of each common factor on observable factors. Most common factors are significantly explained by observable factors from different asset classes. For example, the first factor loads positively on SMB and RMW, and negatively on the stock MOM factor. This is consistent with findings that the negatively correlated HML and MOM are pervasive across various asset classes (Asness, Moskowitz, and Pedersen, 2013), and that HML is largely absorbed when RMW and CMA are controlled for (Fama and French, 2015). It also loads significantly on the credit risk and liquidity risk factors of Dickerson, Mueller, and Robotti (2023). The observable factors explain a substantial

proportion of the variations in common factors, with adjusted R^2 ranging from 19% to 57%, consistent with the high correlations in Table 2. Notably, however, we also find that almost all of the common factors carry additional positive risk premia beyond the observable factors, as reflected in positive intercepts in the regressions. This finding suggests that the common factors capture the additional systematic risks, which are not be fully spanned by existing observable factors.

Next, we extract the principal components from all the observable factors using standard PCA, which displays a strong common factor structure as shown in Appendix A2. We then compare the common factors consistent with the principal components of the observable factors. The top panel of Figure 2 reports the correlations between the two sets of variables. The first common factor (F_1^C) is strongly correlated (above 0.6) with the first principal component ($PC1$), indicating that the two approaches identify the cross-market common variations closely. The bottom panel plots the time series of F_1^C and $PC1$, both of which are pro-cyclical. The two series track each other closely, particularly during the major market stress episodes such as global financial crisis of 2008–09 and COVID-19 pandemic in 2020, when both series decline sharply. This analysis further justifies that common factors capture systematic risks across different asset classes in financial market.

4.1.2 Anatomy of Commonality

To further examine the commonality of the factors, we conduct the cross-market analysis. We first compare common factors with the latent factors estimated from individual asset market, denoted as F^s, F^b, and F^o, respectively.

Table 4 reports the correlations between the two sets of factors. The leading common factor (F_1^C) loads strongly on the latent factors of all asset classes: it is highly correlated with the first stock latent factor (0.85), and also exhibits significant correlations with the first three corporate bond factors (0.62, 0.32, and 0.24) and the first two option factors (0.44 and 0.14). Other common factors also display significant correlations with factors from single 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 weak connection to stock-specific factors. The third common factor likewise exhibits significant correlations with various single-asset-class factors across different markets.

We next examine how asset-class-specific components contribute to the common factors based on the following decomposition:

$$\widehat{\boldsymbol{F}}^{\boldsymbol{C}} = \hat{F}_s^C + \hat{F}_b^C + \hat{F}_o^C = \tilde{R}^{s\prime}\widehat{B}_{cs} + \tilde{R}^{b\prime}\widehat{B}_{cb} + \tilde{R}^{o\prime}\widehat{B}_{co}, \tag{4.1}$$

where $\widehat{\boldsymbol{F}}^{\boldsymbol{C}} = \tilde{\boldsymbol{R}}'\widehat{\boldsymbol{B}}$ with the pooled managed portfolios $\tilde{\boldsymbol{R}} = [\tilde{R}^{s\prime}, \tilde{R}^{b\prime}, \tilde{R}^{o\prime}]'$ and $\widehat{\boldsymbol{B}} = [\widehat{B}'_{cs}, \widehat{B}'_{cb}, \widehat{B}'_{co}]'$ based on (2.5) estimated via regressed-PCA.

Figure 3 plots the coefficients in $\widehat{\boldsymbol{B}}$ associated with the first common factor. The coefficients also represent the portfolio weights of the factor on managed portfolios with the signs indicating the long-short positions. We find that the factor has significant weights on managed portfolios in stocks (19 out of 35), corporate bonds (16 out of 27), and options (13 out of 20), suggesting that F_1^C is a statistically strong factor across markets. Moreover, the finding also indicates that that the first common factor is significantly driven by all three components of (4.1) in different markets, rather than by any single market. The related results for other common factors are reported in Appendix A3, suggesting that the common factors load significantly on managed portfolios of all three asset classes.

Table 5 shows the contribution of each component to (4.1) in the common factors by reporting their correlations and variance decompositions. The first common factor (F_1^C) is highly correlated with its stock (0.89), corporate bond (0.74), and option (0.51) components. A variance decomposition shows that stock component accounts for 57% of the variation in factor returns, followed by corporate bonds (29%) and options (14%). In addition, we also observe that each asset class contributes significantly to the other common factors as well, although the relative proportions vary across factors.

All of these findings indicate that common factors effectively capture substantial cross-market commonalities rather than being tied to any single asset class.

4.2 Economic Relevance

To understand the economic meaning of common factors, we explore their relationship with a broad set of macroeconomic and financial variables, which are key indicators o of the financial market condition. We group these variables into three categories: economic activity indicators, including core inflation, consumption growth (c), and growth in industrial production (IP); 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); financial conditions, including federal funds rate (FFR), term spread (TERM), credit spread (DEF), VIX index, intermediary capital factor (HKM) from He, Kelly, and Manela (2017), and the liquidity factor from Pástor and Stambaugh (2003). Certain series are first-differenced, denoted by $\Delta(\cdot)$, to ensure stationarity.

We examine the economic linkage from two perspectives. First, we examine the explanatory power of the macro-financial variables to common factors, and also analyze the relative contributions of the asset-class-specific constituents to these relations. Second, we forecast and nowcast the macro-financial variables with the common factors. We document that common factors exhibit both strong explanatory and predictive powers to the macro-financial variables, reflecting that their significant relevance to the underlying state of the aggregate economy.

4.2.1 Comovement

Table 6 reports the pairwise correlations between common factors and macro-financial variables, indicating the strong correlations between them. In details, the first common factor is strongly associated with economic uncertainty and intermediary conditions: it is negatively correlated with uncertainty indices and the VIX, and positively correlated with the intermediary capital factor (HKM). Consistent with Figure 2, this finding implies that the first factor is pro-cyclical. The second factor is more sensitive to monetary and credit conditions. It negatively correlates with the federal funds rate and credit spreads, indicating that a tightening monetary shock is associated with a decline in factor returns. In addition, this factor is also negatively related to some uncertainty indexes. The third common factor

shows strong positive associations with core inflation, consumption growth, and industrial production growth, suggesting that it is also pro-cyclical and more impacted by macroeconomic fundamentals. The finding that the factors are pro-cyclical is also compatible with the positive risk premia they carry.

Table 7 summarizes the regression results of the common factors on macro-financial variables. According to the R^2 decomposition, HKM accounts for 29% of explanatory power for the first factor, followed by financial uncertainty (17%) and the term spread (10%).[6] The second factor is mainly explained by the federal funds rate (22%). Both consumption and industrial production growth explain more than 20% of the variance in the third factor. These findings align with the correlations reported in Table 6. The table also shows that macro-financial variables explain substantial variation in the first six common factors, with adjusted R^2 ranging from 16.26% to 38.6%. We also compare common factors with macroeconomic factors in Ludvigson and Ng (2009) in Appendix A4, further revealing the strong links between common factors and macro fundamentals.

The decomposition in (4.1) allows us to identify which asset-class-specific components drive the comovement between common factors and different macro-financial variables. In particular, we regress asset-class-specific constituents of the first common factor on macro-financial variables, where the results are reported in Table 8. We find that the positive comovement between the first factor and HKM factor is driven primarily by the stock and corporate bond components. The negative association of the first factor with macro and economic policy uncertainty is attributable to its corporate bond component, while the negative correlations with the VIX and financial uncertainty come mainly from the option components. Moreover, a substantial variation in the three components can be explained by macro-financial variables with the adjusted R^2: 24.42%, 41.16% and 22.89%, separately.

4.2.2 Forecasting and Nowcasting

We further evaluate common factors' forecasting and nowcasting performance to the macro-financial variables. We test their forecasting ability using the following expanding window

[6]See more details in Huettner and Sunder (2012) and Fournier, Jacobs, and Orłowski (2024) on the Shapley–Owen R^2 decomposition.

regression through time t:

$$Y_t = \gamma_t^f + \Gamma_t^{f\prime} \hat{f}_{t-1}^C + \varepsilon_t^f, \tag{4.2}$$

where Y_t denotes a macro-financial variable of interest, and $\hat{f}_{t-1}^C$ is the one-period lagged common factors. We test the predictive power of common factors with the predictive regression: $Y_{t+1} = a^f + \beta^{f\prime} \hat{Y}_{t+1|t} + \varepsilon_{t+1}^f$, where $\hat{Y}_{t+1|t} = \hat{\gamma}_t^f + \hat{\Gamma}_t^{f\prime} \hat{f}_{t-1,t}^C$.[7]

For nowcasting, the procedure is analogous but utilizes contemporaneous information. We first conduct the contemporaneous regression: $Y_{t-1} = \gamma_{t-1}^N + \Gamma t - 1^{N\prime} \hat{f}_{t-1}^C + \varepsilon_{t-1}^N$, and assess nowcasting performance with the regression: $Y_t = a^N + \beta^N \hat{Y}_t + \varepsilon_t^N$, where the nowcast is defined as $\hat{Y}_t \equiv \hat{\gamma}_{t-1}^N + \hat{\Gamma}_{t-1}^{N\prime} \hat{f}_{t-1,t}^C$.

Table 9 reports the regression results with $K = 10$.[8] Panel I shows that the common factors have significant forecasting power for macroeconomic variables, especially core inflation, consumption growth, and industrial production growth. Panel II shows that the factors are effective in nowcasting financial variables: HKM, $\Delta(VIX)$, and $\Delta(FINU)$. These results suggest that the common factors contain both forward-looking information on macroeconomic environment and contemporaneous information on financial conditions. In particular, the table also shows that the factors are informative for monetary policy, which exhibit significant both forecasting and nowcasting powers to $\Delta(FFR)$.

5 Pricing Cross-Sectional Returns

In this section, we evaluate the performance of the common factors in jointly pricing the cross-sectional returns across different markets. We examine the goodness-of-fit and predictability of common factors for individual asset returns. We also test the significance of mispricing errors, and construct a pure-*alpha* strategy accordingly.

[7] $\hat{f}_{t-1,t}^C$ is out-of-sample realized factors at time t, defined in .

[8] In (4.2), we winsorize Y_t at the 1% and 99% levels to ensure stability, particularly for the extreme values during episodes like COVID-19. While Y_{t+1} is not winsorized in the prediction. It is similar for nowcasting.

5.1 Factor Pricing

We begin by defining several measures to evaluate the in-sample and out-of-sample performance of the common factor model in (2.5). For in-sample fit, we first calculate the Fama-MacBeth cross-sectional regression R^2, denoted as $R^2_{\tilde{R}}$, measuring how well the pooled characteristic-managed portfolios explain the variation in individual asset returns across all markets. We next report the variation in these managed portfolios explained by the common factors, denoted as R^2_K. To assess the ability of common factors to explain the cross-section of individual asset returns, we define the total R^2 as:

$$R^2 = 1 - \frac{\sum_{i,t}[r_{i,t} - \hat{\alpha}(z_{i,t-1}) - \hat{\beta}(z_{i,t-1})'\hat{f}_t]^2}{\sum_{i,t} r_{i,t}^2}. \tag{5.1}$$

The out-of-sample analysis is based on expanding window estimation. 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 further $\hat{\alpha}_{t-1}(z_{i,t-1}) = \hat{a}'_{t-1} z_{i,t-1}$, $\hat{\beta}_{t-1}(z_{i,t-1}) = \hat{B}'_{t-1} z_{i,t-1}$. To assess the performance of factor portfolios, we construct the tradable out-of-sample factors as:

$$\hat{f}_{t-1,t} = \hat{B}'_{t-1}(Z'_{t-1}Z_{t-1})^{-1}Z'_{t-1}R_t = \hat{B}'_{t-1}\tilde{R}_t. \tag{5.2}$$

We evaluate the out-of-sample fit with the following alternative out-of-sample realized factors at time t:

$$\hat{f}_{t-1,t} = \left[(Z_{t-1}\hat{B}_{t-1})'(Z_{t-1}\hat{B}_{t-1})\right]^{-1}(Z_{t-1}\hat{B}_{t-1})'(R_t - Z_{t-1}\hat{a}_{t-1}). \tag{5.3}$$

which is asymptotically equivalent to (5.2).

We consider three types of R^2 to assess the fitness of $\hat{f}_{t-1,t}$: $R^2_{f,O}$ directly evaluates the total out-of-sample fit; $R^2_{f,T,N,O}$ measures the cross-sectional average of time-series fit to all individual assets; $R^2_{f,N,T,O}$ measures the time-series average of cross-sectional fit. The measures are given by

$$\begin{aligned}
R^2_{f,O} &= 1 - \frac{\sum_{i,t\geqslant 60}[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_{i,t\geqslant 60} r_{i,t}^2}, \\
R^2_{f,T,N,O} &= 1 - \frac{1}{N}\sum_i \frac{\sum_{t\geqslant 60}[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_{t\geqslant 60} r_{i,t}^2}, \\
R^2_{f,N,T,O} &= 1 - \frac{1}{T-60}\sum_{t\geqslant 60} \frac{\sum_i[r_{i,t} - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{f}_{t-1,t}]^2}{\sum_i r_{i,t}^2}.
\end{aligned} \tag{5.4}$$

We further predict $r_{i,t}$ with $\hat{\alpha}_{t-1}(z_{i,t-1}) - \hat{\beta}_{t-1}(z_{i,t-1})'\hat{\lambda}_t$, where $\hat{\lambda}_t = \sum_{s\leqslant t-1} \hat{f}_s^{(t-1)}/(t-1)$. The out-of-sample predictive measures are similarly defined by replacing $\hat{f}_{t-1,t}$ with $\hat{\lambda}_t$ in (5.4), which are denoted as: R^2_O, $R^2_{N,T,O}$, $R^2_{N,T,O}$, respectively.

In Table 10, we report the in-sample and out-of-sample annualized Sharpe ratios of common factors, where the out-of-sample realized factors are defined in (5.2). We find that the common factors carry substantial risk premia, with their high Sharpe ratios are mainly driven by option components. For instance, the maximal in-sample and out-of-sample Sharpe ratios achieve 1.28 and 2.51, where the Sharpe ratios of corresponding option components are 2.63 and 2.87, respectively. Meanwhile, Table 10 also shows the larger both in-sample and out-of-sample Sharpe ratios of option factors compared to the stock and corporate bond factors.

Table 11 reports the performance of common factors in explaining and predicting cross-sectional individual returns across and within different markets. First, common factors explain substantial in-sample variations of managed portfolios across asset classes. As the number of factors (K) increases to ten, R^2_K rises from 15.21% to 67.01%, which also monotonically increases in each asset class (stock: 21.85% to 67.73%; corporate bond: 13.45% to 65.12%; option: 8.82% to 67.97%). In particular, with ten factors, the closely aligned explanatory abilities (R^2_K) for the three markets indicate that the common factors effectively capture cross-market commonality. Second, in-sample fit for individual asset returns improve as K increase: the total R^2 rises from 6.11% to 16.76% for the pooled individual assets, from 6.27% to 11.51% for stocks, from 11.21% to 33.99% for corporate bonds, and from 5.40% to 19.53% for options. The ability of common factors to capture substantial variations in both managed portfolios and individual assets reinforces the prevalence of these factors across markets, as documented in Section 4.

Moreover, the common factors exhibit strong out-of-sample fit: the ten realized out-of-sample factors in (5.3) account for 5.42%, 12.85% and 8.15% of the variation in the joint cross-section of next-period returns, as measured by $R^2_{f,O}$, $R^2_{f,T,N,O}$ and $R^2_{f,N,T,O}$, respectively. We also document the strong out-of-sample fit of $\hat{f}_{t-1,t}$ in each asset class. Across the three markets, the out-of-sample fit is relatively weaker for option returns ($R^2_{f,O}$: 1.19% to 3.49%)

compared to stock and corporate bond returns ($R^2_{f,O}$: 9.49% to 12.00% and 2.40% to 17.43%), which might be due to the short time-to-maturity or illiquidity of many options.

Lastly, Table 11 also shows the strong joint predictability of the common factors for individual returns across all markets: R^2_O: 0.20%; $R^2_{N,T,O}$: 0.39%; $R^2_{N,T,O}$: 0.35%. The joint predictability is particularly strong for corporate bonds followed stocks and options. In Table A5, we report the corresponding results for for the asset-class-specific factor models in (2.3). We find that common factors exhibit comparable both in-sample and out-of-sample fit compared to single-asset-class factors for all asset markets. This comparison indicates that the cross-asset commonality is largely captured by the common factors.

5.2 Mispricing

In the previous section, we document that a large proportion of cross-sectional variations in individual asset returns and managed portfolios is explained by common factors. Now, we examine whether the cross-section of individual asset or managed portfolio returns can be fully spanned by common factors by testing $\boldsymbol{a} = 0$ in (2.5) using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2021). Figure 4 reports the in-sample estimation of coefficients ($\hat{\boldsymbol{a}}$) and the associated 95% confidence intervals with $K = 10$. After controlling for ten common factors, the pooled mispricing error still loads significantly on many characteristics (stock: 12 out of 35; corporate bond: 14 out of 27; option: 15 out of 20), rejecting the null $\boldsymbol{a} = 0$. Importantly, it indicates that common factors cannot fully span the cross-sectional asset returns across markets, although they carry sizable risk premia and display strong in-sample and out-of-sample performance in Section 5.1. This finding also highlights the significant anomalies in all markets, especially the option market.

Chen, Roussanov, and Wang (2021) demonstrate that the rejection of $\boldsymbol{a} = 0$ implies an "arbitrage" portfolio with weight at time t given by:

$$\boldsymbol{w}^{\alpha}_t = \boldsymbol{Z}_t \left(\boldsymbol{Z}'_t \boldsymbol{Z}_t\right)^{-1} \hat{\boldsymbol{a}}_t, \tag{5.5}$$

where $\hat{\boldsymbol{a}}_t = (\hat{a}'_{cs,t}, \hat{a}'_{cb,t}, \hat{a}'_{co,t})'$ is estimated using data through t. This joint pure-*alpha* trading strategy is an asymptotic "arbitrage" portfolio since $\boldsymbol{w}^{\alpha\prime}_t \boldsymbol{R}_{t+1} = \hat{\boldsymbol{a}}'_t \tilde{\boldsymbol{R}}_{t+1} \to_p \|\boldsymbol{a}\|^2$ as $N \to \infty$ at each time. Essentially, this "arbitrage" portfolio exploits the predictive power of the

characteristics as in Daniel and Titman (1997), while it has zero exposure or is orthogonal to the common factors by noting $\hat{\boldsymbol{a}}'_t\hat{\boldsymbol{B}}_t = 0$. Moreover, to identify the sources of "arbitrage" across different asset markets, we decompose the joint pure-*alpha* strategy into:

$$\hat{\boldsymbol{a}}'_t\tilde{\boldsymbol{R}}_{t+1} = \hat{a}'_{cs,t}\tilde{R}^s_{t+1} + \hat{a}'_{cb,t}\tilde{R}^b_{t+1} + \hat{a}'_{co,t}\tilde{R}^o_{t+1}. \tag{5.6}$$

From Figure 4, we also find that the option component in (5.6) contributes significantly to the joint "arbitrage" portfolios: $\mathrm{Cov}(\hat{a}'_{co,t}\tilde{R}^o_{t+1}, \hat{\boldsymbol{a}}'_t\tilde{\boldsymbol{R}}_{t+1})/\mathrm{Var}(\hat{\boldsymbol{a}}'_t\tilde{\boldsymbol{R}}_{t+1}) = 73.86\%$, and $\|\hat{a}_{co}\|^2/\|\hat{\boldsymbol{a}}\|^2$: 61.58%. By contrast, the limited contribution of corporate bond component is in line with recent evidence (e.g., Dickerson, Robotti, and Rossetti, 2023) showing that many bond return anomalies diminish once microstructure noise is addressed. Stock component contributes modestly to the returns of "arbitrage" portfolio, consistent with the relatively high liquidity and competitive nature of equity market, where anomalies are quickly arbitraged away.

Table 12 reports the out-of-sample annualized means, standard deviations, and Sharpe ratios of the joint pure-*alpha* strategies and associated components specified in (5.6). The joint portfolio delivers a substantially high out-of-sample Sharpe ratio of 2.14. Expanding the number of factors does not eliminate this effect: even after controlling for ten common factors, the pure-*alpha* portfolio continues to achieve a Sharpe ratio close to 2. However, the Sharpe ratios display a U-shaped pattern with increasing of K. As K increases from one to five, the decline in Sharpe ratios (from 7.50 to 3.07) suggests that factors absorb substantial expected asset returns, reducing the returns of pure-*alpha* portfolio at a rate that exceeds the decline in volatility. In contrast, as K increases from six to ten, the rise in Sharpe ratios (from 3.06 to 3.52) results from the factors absorbing covariation of asset returns at a higher rate than the decline in alphas. Based on the decomposition in (5.6), we find that the high Sharpe ratios of pure-*alpha* portfolios are mainly contributed by options, which is also consistent with the in-sample results shown in Figure 4. Overall, the consistently high Sharpe ratios of the pure-*alpha* strategy reveal that a significant portion of the cross-sectional asset returns remains unexplained by common factors, aligning with the testing results: rejection of $\boldsymbol{a} = 0$.

6 Constructing Joint MVE Portfolios

In this section, we construct conditional mean–variance efficient (MVE) portfolios jointly across stocks, corporate bonds, and options based on the common factor model in (2.5). We then evaluate the in-sample and out-of-sample performance of the joint MVE portfolios and analyze their hedging properties across different asset classes. We further identify the sources of the hedging by examining the exposure of joint MVE portfolios to common factors.

Specifically, the conditional joint MVE portfolio problem at time t is

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

where the optimal weight is given by $\boldsymbol{w}_t = \operatorname{Var}_t \left[\boldsymbol{R}_{t+1} \right]^{-1} E_t \left[\boldsymbol{R}_{t+1} \right]$ with $\boldsymbol{R}_{t+1}$ denoting the individual excess returns across classes.

However, constructing MVE portfolios directly from individual assets is challenging, as it requires estimating a high-dimensional sample covariance matrix. Given a large cross-section of assets but relatively short time series, the estimation of covariance matrix is unstable and imprecise, and the out-of-sample analysis is not even feasible. These challenges are more pronounced in a joint setting across different asset classes, where many securities, particularly options, have short trading histories and unbalanced panels. Existing approaches based on the estimation of large-dimensional covariance matrices (e.g., Ledoit and Wolf, 2017) are generally applicable to a single asset class with balanced panels. Therefore, these methods are less suitable for the multiple asset classes with unbalanced panels.

We address these challenges by exploiting the factor structure in (2.5). Our approach has two advantages. First, the model in (2.5) directly incorporates characteristics into portfolio construction, thereby improving the approximation of conditional MVE portfolios. In contrast, traditional methods (e.g., Ledoit and Wolf, 2017) do not capture this conditional information. Second, our approach translates the problem of covariance matrix estimation for a high-dimensional unbalanced panel into the estimation for a low-dimensional set of common factors.

Under the assumption that the idiosyncratic errors are homoskedastic and uncorrelated

across different asset classes, i.e. $\text{Var}_t(\boldsymbol{\xi}_{t+1}) = \sigma_t^2 \boldsymbol{I}$, the problem in (6.1) can be expressed as

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

where $\tilde{\boldsymbol{R}}_{t+1} = (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \boldsymbol{Z}_t' \boldsymbol{R}_{t+1}$. The optimal weight now is

$$\boldsymbol{w}_t = \boldsymbol{Z}_t (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \tilde{\boldsymbol{b}}_t, \tag{6.3}$$

with $\tilde{\boldsymbol{b}}_t = \left[\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] + \sigma_t^2 (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \right]^{-1} E_t[\tilde{\boldsymbol{R}}_{t+1}]$.[9] Hence, the optimal portfolio choice over large cross-sectional individual assets reduces to portfolio choice over a much smaller set of characteristic-managed portfolios resulting from Fama-MacBeth regression. The term $\sigma_t^2 (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1}$ reflects the effect of idiosyncratic errors. However, with a large set of characteristics in the model (2.5), estimation of the managed portfolio covariance matrix remains potentially unstable, especially for out-of-sample analysis. Based on the common factor structure in (2.5), we can further approximate the covariance matrix with

$$\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] = \boldsymbol{B} \, \text{Var}_t \left[f_{t+1}^C \right] \boldsymbol{B}'. \tag{6.4}$$

Since the regressed-PCA does not require large T, both in-sample and out-of-sample covariance matrices of the common factors can be consistently estimated even with a relatively short time series. The in-sample estimate of the conditional variance of idiosyncratic errors is given by $\hat{\sigma}_{t+1}^2 = \frac{1}{N-1} \sum_{i=1}^N (R_{i,t+1} - Z_{i,t}' \tilde{\boldsymbol{R}}_{t+1})^2$. For out-of-sample analysis, we predict σ_{t+1}^2 with $\hat{\sigma}_t^2$, assuming $E_t[\sigma_{t+1}^2] = \sigma_t^2$. We also construct MVE portfolios separately for each asset class by approximating the corresponding covariance matrices using asset-class-specific latent factors estimated from (2.3).

Panel I of Table 13 reports the annualized Sharpe ratios of joint and asset-class-specific MVE portfolios constructed with ten factors. 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 asset-class-specific MVE portfolios (stock: 2.98; corporate bond: 1.58; option: 2.64). To better understand the sources of gains in Sharpe ratios, we decompose the joint MVE portfolio in (6.3) into

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

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

[9] See Proof 1 in Appendix

Panel I shows that stock (2.08) and option (2.81) components deliver relatively higher Sharpe ratios compared to the corporate bond (1.05) component in the joint MVE portfolio. This is also consistent with Panel II of the table, which shows that the joint MVE portfolio is strongly correlated with its stock and option constituents, but not with its bond component. The low correlation is explained by the finding that the bond constituent is significantly and negatively correlated with both stock (-0.16) and option (-0.32) constituents. Importantly, this finding suggests that the bond component hedges against equity and option components, significantly reducing volatility and increasing the Sharpe ratio of the joint MVE portfolio, despite its own low return as well as Sharpe ratio. Although the hedging between stock and option components is relatively weak (-0.03), the large covariance resulting from their high standard deviations still significantly lowers the volatility of the joint MVE portfolio. Taken together, cross-market diversification reduces the volatility of joint MVE portfolio, accounting for its superior efficiency relative to asset-class-specific MVE portfolios.

Panel III of Table 13 shows that the bilateral hedging properties among the asset-class-specific constituents can be explained by their offsetting exposures to the common factors. In particular, the hedging between the stock (option) and corporate bond components arises primarily from opposite loadings on the first (fourth) common factor: –0.30 and 0.36 (–0.26 and 0.38). The weak hedging between stock and option constituents is explained by that the negative correlation resulting from their significantly opposite loadings on the second factor (-0.18 and 0.19) is offset by their positive comovement driven by six other common factors. Alternatively, diversification among different components can also be attributable to their opposing long-short positions on common factor portfolios, as reflected in the signs of their correlations. The table further shows that the joint MVE portfolio has negligible correlations with most common factors, indicating that the exposures of different components largely cancel each other out. Consequently, the joint MVE portfolio bears almost zero factor exposures, which justifies its efficiency and superiority.

Next, we turn to the out-of-sample analysis of the joint MVE portfolios based on the same expanding window estimation in Section 5. Figure 5 shows that the Sharpe ratios of the out-of-sample MVE portfolios increase with the number of factors increasing from 1 to 20, reaching the peak of 2.94 at $K = 14$. More details are reported in Table A17, which shows

that the joint MVE portfolios outperform any single-asset-class MVE portfolios when $K \geqslant 12$. This observation indicates that using a larger set of factors more effectively captures the hedging relationships among different components, thereby reducing the portfolio volatility. Similar to the in-sample analysis, we examine the source of out-of-sample hedging properties based on the out-of-sample factors in (5.3). Given $K = 20$, Table A20 confirms that the hedging relationship can be explained by offsetting positions on the out-of-sample factors. Table A17 further shows that the Sharpe ratios of the stock and option components in the joint out-of-sample MVE portfolios are larger, as the in-sample results in Table 13.

7 Measuring Market Segmentation

The strong common factor structure across markets raises a natural question: does the strong cross-market commonality captured by these factors reflect a large extent of market integration? In this section, we formally measure cross-market integration or segmentation with market distances based on the common factor structure in (2.5). We demonstrate that the market distance can be measured by the heterogeneous risk premia of common factors across markets, where the significant segmentation between markets is documented.

7.1 Measurement

Building on Chen and Knez (1995), we measure market segmentation as the minimum squared distance between the sets of admissible stochastic discount factors (SDFs) between markets. For markets $A, B \in \{s, b, o\}$, the distance is defined as

$$d(\mathcal{M}^A, \mathcal{M}^B) = \min_{m^A \in \mathcal{M}^A,\, m^B \in \mathcal{M}^B} \|m^A - m^B\|^2, \tag{7.1}$$

where $\mathcal{M}^A$ and $\mathcal{M}^B$ denote sets of admissible SDFs in the two markets.[10] They further show that this measure can also be expressed in terms of how differently the two markets

[10]For market $X \in \{A, B\}$, the set of admissible SDFs $\mathcal{M}^X = M^X + \mathcal{R}^{X\perp}$, where M^X denotes the SDFs in the excess return spaces $\mathcal{R}^X$, and $\mathcal{R}^{X\perp}$ denotes the orthogonal complements of $\mathcal{R}^X$. For any $m^X \in \mathcal{M}^X$, there exists $\epsilon^X \in \mathcal{R}^{X\perp}$ such that $m^X = M^X + \epsilon^X$ and $E_t[m^X_{t+1} R^X_{t+1}] = E_t[M^X_{t+1} R^X_{t+1}] = 0$ for any $R^X \in \mathcal{R}^X$ at time t. The sets of admissible SDFs for stock, corporate bond and option markets can be defined similarly, denoted as $\mathcal{M}^s$, $\mathcal{M}^b$ and $\mathcal{M}^o$, respectively.

price their common payoff.[11] Let $\mathcal{F}^{AB} \equiv \mathcal{R}^A \bigcap \mathcal{R}^B$ be the common payoff span of the excess returns in two markets with a set of orthogonal basis f, the market distance in (7.1) is equivalent to

$$\begin{aligned} d(\mathcal{M}^A, \mathcal{M}^B) &= \left(\pi_A(f) - \pi_B(f)\right)' E[ff']^{-1} \left(\pi_A(f) - \pi_B(f)\right) \\ &= (\lambda_B - \lambda_A)' E[ff']^{-1} (\lambda_B - \lambda_A), \end{aligned} \tag{7.2}$$

where $\pi_X(f) = E[M^X \cdot f]$ and $\lambda_X = -\operatorname{Cov}(M^X, f)$ are the pricing errors and risk premia of f according to M^X in market $X \in \{A, B\}$.

Markets A and B are perfectly integrated if and only if $\mathcal{M}^A \bigcap \mathcal{M}^B$ is nonempty, or equivalently, $d(\mathcal{M}^A, \mathcal{M}^B) = 0$. Importantly, the common factors form an orthogonal basis of common payoff space $\mathcal{F}^C \equiv \mathcal{R}^s \bigcap \mathcal{R}^b \bigcap \mathcal{R}^o$ under the orthogonality conditions $f^C \perp \xi^s \perp \xi^b \perp \xi^o$ in (2.4).[12] We therefore use the common factors as the benchmark payoffs in (7.2) such that the extent of market segmentation is measured by the discrepancy of common factor risk premia between two markets. Notably, this indicates that the extent of segmentation is not directly related to the time-series comovement captured by the common factors between two markets. Put differently, even if the common factors explain substantial cross-market covariation, markets can still be highly segmented because common factor risk premia differ across them.

Next, we construct the SDF in (7.2) with the assumption that the law of one price (LOP) holds within each asset market and the normalization $E_t[M_{t+1}] = 1$. Under these conditions, Hansen and Jagannathan (1997) show that the unique SDF in the span of R_{t+1} is affine in excess returns:

$$M_{t+1} = 1 - w_t' \left(R_{t+1} - E_t\left[R_{t+1}\right]\right), \tag{7.3}$$

with w_t given as in (6.1) for a single market. In practice, constructing SDFs faces the same challenges as constructing MVE portfolios, which is mentioned in Section 6. Assuming homoscedasticity in (2.3), we can approximate the SDF in each market with its managed portfolios by following Kozak and Nagel (2023). They show that the SDF can be spanned by the managed portfolios under certain conditions.[13] As a result, the SDF in (7.3) can be

[11] See Theorem 3 and Corollary 2 in Chen and Knez (1995).

[12] See Proof 2 in Appendix.

[13] Since the covariance matrix estimation for unbalanced panels is infeasible, we assume homoscedastic er-

approximated as

$$M_{t+1} = 1 - \tilde{b}_t' \left(\tilde{R}_{t+1} - E_t[\tilde{R}_{t+1}] \right), \tag{7.4}$$

where $\tilde{b}_t$ is given as in (6.3) for a single market.

However, misspecification of SDFs resulting from the homoscedasticity assumption shall distort the estimates of market distance. To address this issue, we gauge the violation of integration based on the distance between the admissible SDF sets on the managed portfolios return spaces ($\widetilde{\mathcal{R}}^A$ and $\widetilde{\mathcal{R}}^B$), which are denoted as $\widetilde{\mathcal{M}}^A$ and $\widetilde{\mathcal{M}}^B$, separately. Since $\widetilde{\mathcal{R}}^X \subseteq \mathcal{R}^X$ and $\mathcal{M}^X \subseteq \widetilde{\mathcal{M}}^X$ for market $X \in \{A, B\}$, it follows $d(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B) \leqslant d(\mathcal{M}^A, \mathcal{M}^B)$.[14] Therefore, the rejection of integrated markets of $\widetilde{\mathcal{R}}^A$ and $\widetilde{\mathcal{R}}^B$ implies the rejection of integrated markets of $\mathcal{R}^A$ and $\mathcal{R}^B$. Meanwhile, the orthogonality conditions $f^C \perp \xi^s \perp \xi^b \perp \xi^o$ in (2.4) further imply that $\widetilde{\mathcal{F}}^C = \mathcal{F}^C$ such that common factors also form an orthogonal basis of $\widetilde{\mathcal{F}}^C \equiv \widetilde{\mathcal{R}}^s \bigcap \widetilde{\mathcal{R}}^b \bigcap \widetilde{\mathcal{R}}^o$. Common factors then can also be used to measure $d(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B)$ for markets $A, B \in \{s, b, o\}$.

We additionally measure the market distance using pairwise factors f^{AB} as the common payoff basis for markets $A, B \in \{s, b, o\}$. Under the orthogonality conditions $f^{AB} \perp \xi^A \perp \xi^B$, f^{AB} form an orthogonal basis of common payoff space $\mathcal{F}^{AB} = \mathcal{R}^A \bigcap \mathcal{R}^B$, where the detailed estimation results are shown in Appendix A5.

Lastly, we propose the test statistic for the market distance and derive its asymptotic distribution. The market segmentation measure in (7.2) resembles the population Hansen-Jagannathan (HJ) distance for $\breve{M}^{A,B}$ on test assets f, where $\breve{M}^{A,B} = M^A - M^B$, and f are common factors or pairwise factors. Under the null of market integration and certain regularities, we can derive the asymptotic distribution of $T\hat{d}(\mathcal{M}^A, \mathcal{M}^B)$ as:

$$T\hat{d}(\mathcal{M}^A, \mathcal{M}^B) \longrightarrow_d \sum_{k=1}^{K} \tau_k \chi_k^2(1), \tag{7.5}$$

where τ_k is the k-th eigenvalue of $V^{1/2} E_t[f_t f_t']^{-1} V^{1/2}$ with covariance matrix $V = E_t[(\breve{M}_t^{A,B})^2 f_t f_t']$ or long-run covariance matrix $V = \sum_{j=-\infty}^{\infty} E_t[\breve{M}_t^{A,B} \breve{M}_{t+j}^{A,B} f_t f_{t+j}']$ by considering the time de-

rors in (2.4). As in Kozak and Nagel (2023), we mitigate the impact of unpriced components by incorporating a large set of characteristics such that managed portfolios approximate the underlying SDF well.

[14] Under the specification in (2.4), the equality holds if expected returns are fully captured by characteristics, that is, $E_t[R_{t+1}^X] = Z_t^{X\prime} E_t[\tilde{R}_{t+1}^X]$, and $\tilde{R}^X \perp \xi^X$ for market $X \in \{s, b, o\}$. See Proof 3 in Appendix.

pendence, and $\chi_1^2(1), \ldots, \chi_K^2(1)$ are independent $\chi^2(1)$ random variables.[15] The asymptotics distribution of test statistics with $d(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B)$ can be derived similarly.

7.2 A Regression Approach

In this section, we demonstrate that the market distance can be equivalently measured by the cross-market price dispersion of common factors. Common factors are tradable portfolios in all three markets by noting $f^C \in \widetilde{\mathcal{F}}^C = \mathcal{F}^C$ under the orthogonality conditions, which can also be represented with the basis of $\widetilde{\mathcal{R}}^X$ in each market $X \in \{s, b, o\}$ as:

$$f_t^C = \delta_X^C + \Gamma_X^C \tilde{R}_t^X, \text{ for } t = 1, ..., T, \tag{7.6}$$

where the projections $\Gamma_X^C \tilde{R}_t^X$ are the mimicking portfolios of f_t^C in the market X, and projection errors δ_X^C are the prices of f_t^C assigned by market X, that is, $E_t[M_t^X f_t^C] = E_t[\tilde{M}_t^X f_t^C] = \delta_X^C$ based on LOP within each market. With the extracted common factors $\widehat{f}_t^C$, we estimate δ_X^C using the following regression:

$$\widehat{f}_t^C = \delta_X^C + \Gamma_X^C \tilde{R}_t^X + \varepsilon_t^{Xf}. \tag{7.7}$$

Notably, for markets $A, B \in \{s, b, o\}$, the null hypothesis of the integrated market implies that $d(\widetilde{\mathcal{M}}^A \widetilde{\mathcal{M}}^B) = 0$, which is equivalent to $\delta_A^C - \delta_B^C = 0$. Based on the regression in (7.7), we then construct the following Wald statistics:

$$T(\hat{\delta}_A^C - \hat{\delta}_B^C)' \hat{V}_{AB}^{-1} (\hat{\delta}_A^C - \hat{\delta}_B^C) \to_d \chi^2(K), \tag{7.8}$$

where $\hat{V}_{AB}^{-1}$ and the derivations are shown in Appendix.[16]

Similar to Section 7.1, we extend this analysis to pairwise factors, f^{AB}. Under the null hypothesis, LOP holds both within and across markets, and there exists an SDF $M^{A,B} \in \mathcal{M}^A \bigcap \mathcal{M}^B$ such that $E_t[M_t^{A,B} f_t^{AB}] = E_t[M_t^X f_t^{AB}] = 0$ for $X \in \{A, B\}$ at each time t. Importantly, this means that zero-cost portfolios $f^{AB} \in \mathcal{R}^A \bigcap \mathcal{R}^B$ have a price of zero in both markets A and B. Moreover, cross-market LOP also implies that LOP also holds on managed portfolio return spaces, therefore, f^{AB} also have zero prices in the spaces both $\widetilde{\mathcal{R}}^A$ and $\widetilde{\mathcal{R}}^B$ based on a similar argument. To test these pricing implications, we estimate an

[15] See Proof 4 in Appendix.
[16] See Proof 5 in Appendix.

analogue of (7.7), replacing the common factors with the estimated pairwise factors $\widehat{f}_t^{AB}$. Denoting the intercepts as δ_X^{AB}, we then test the hypotheses $\delta_X^{AB} = 0$ and $\delta_A^{AB} - \delta_B^{AB} = 0$ for $X \in \{A, B\}$ and $A, B \in \{s, b, o\}$, as in (7.8).

Our framework is closely related to recent studies (Choi and Kim, 2018; Sandulescu, 2019) that gauge market segmentation by comparing the prices of portfolios in a certain market according to the SDF in another market, that is, $E_t[\tilde{M}_t^A \tilde{R}_t^B] = E_t[\tilde{M}_t^B \tilde{R}_t^A] = 0$ or $E_t[\tilde{M}_t^A \tilde{R}_t^B] - E_t[\tilde{M}_t^B \tilde{R}_t^A] = 0$. A key difference is that we employ the common factors or pairwise factors as benchmark payoffs to gauge the market distances, that is, $E_t[\tilde{M}_t^A \hat{f}_t] - E_t[\tilde{M}_t^B \hat{f}_t] = 0$ or $E_t[\tilde{M}_t^X \hat{f}_t] = 0$ for $X \in \{A, B\}$. We show that our framework is not equivalent to others discussed in the Appendix[17]

7.3 Results

Table 14 reports the estimation results of market distances based on (7.2). In Panel I and II, the market distances are computed using common factors of all asset classes ($\boldsymbol{F}^C$) and the respective pairwise factors (F^{AB}), separately, where the left part of each panel reports the results with SDFs constructed based on (7.4) in the span of individual asset excess returns and the right part reports the results with SDFs in the span of managed portfolio return spaces. Overall, Panel I shows significant evidence of cross-market segmentation. First, the distances increase with the number of factors K for both sets of factors, which is because that the expansion of significant common payoff space captures more pricing inconsistencies. Second, in both sets of factors with $K \geqslant 2$, the estimated distances between the option and corporate bond markets are statistically significant and remain the largest among all market pairs, while the distances between the stock and corporate bond markets are the closest and consistently insignificant. The distances of stock and option markets are in-between, which are significant based on $\hat{d}(\mathcal{M}^A, \mathcal{M}^B)$ but less so based on $\hat{d}(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B)$. These results suggest that the option market is highly segmented from corporate bond market but less segmented from stock market, while the degree of segmentation between stock and corporate bond markets is much weaker. Third, we observe the violation of inequality $\hat{d}(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B) \leqslant$

[17] See Proof 6 in Appendix.

$\hat{d}(\mathcal{M}^A, \mathcal{M}^B)$ in empirical results, which might be due to the model misspecification and estimation errors.

Panel II also shows that all market pairs are significantly segmented. Consistent with Panel I, we observe that the market distances increase with the number of factors, and the discrepancy of common factor risk premia in stock and corporate bond markets are relatively smaller compared to other market pairs. There are several notable findings. First, with $K \geqslant 5$, the market distances based on pairwise factors are larger than these based on common factors, while the associated p-values based on F^{AB} are smaller. Second, different from Panel I, the distances between stock and corporate bond markets are statistically significant at the 5% level based on $\hat{d}(\mathcal{M}^A, \mathcal{M}^B)$, and at the 10% level based on $\hat{d}(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B)$ when $K \geqslant 8$; the distances between stock and option markets are significant at the 5% level for both sets of factors when $K > 8$. Put together, all of these findings indicate the larger and stronger extent of segmentation based on pairwise factors. This is because pairwise factors capture additional common variation between the respective market pairs, i.e., pairwise-factors, which are absent in common factors as shown in Table A7-A8.

Table 15 shows the testing results based on the regression approach in (7.7), which reports the t-statistics and p-values of GRS-test (Gibbons, Ross, and Shanken, 1989) for $\delta_X^{AB} = 0$ and p-values of test in (7.8) for $\delta_A^{AB} - \delta_B^{AB} = 0$. Based on the common factors with $K \geqslant 2$, the rejections of $\delta_X^C - \delta_o^C = 0$ for $X \in \{s, b\}$ imply that option market is significantly segmented from both stock and corporate bond markets. Meanwhile, $\delta_s^C - \delta_b^C$ is not significantly away from zero, indicating the insignificant price dispersion of common factors between stock and corporate bond markets. Based on pairwise factors, we find the evidence of significant segmentation of all market pairs, that is, $\delta_A^{AB} - \delta_B^{AB} = 0$ is rejected for $A, B \in \{s, b, o\}$. In particular, the integrated stock and corporate bond markets are rejected based on pairwise factors with $K \geqslant 7$. All of these results are consistent with the findings in Table 14. Table 15 further shows that δ_b^{sb}, δ_s^{so} and δ_b^{bo} are significantly away from zeros. Importantly, these findings highlight the source of price dispersions. For instance, the rejection of $\delta_s^{so} = 0$ indicates the price of f^{so} in stock market is different from zero. In sum, the conclusions based on two different approaches in (7.2) and (7.7) are highly consistent.

Overall, the conclusions are robust to the choice of factor in the measure of (7.2). The

significant distances may reflect underlying market frictions. One possible explanation pf the segmented markets is limits to arbitrage, as emphasized by Kapadia and Pu (2012) and Siriwardane, Sunderam, and Wallen (2025), which can prevent the LOP from holding across markets. Another potential explanation is the specialization of dealers in different markets, as discussed by Wittwer and Uthemann (2025), which may restrict cross-market arbitrage activity and generate market segmentation. We provide a formal measure of these frictions: the estimated market distances quantify the extent to which the pricing of common risk factors varies across markets. Our framework explicitly informs the magnitude and source of market segmentation, without relying on model assumption and environment.

8 Conclusion

In this paper, we identify a strong common factor structure across major corporate securities: stocks, corporate bonds, and options. We extract common factors jointly from individual asset returns via the regressed-PCA in a conditional factor model across three asset markets.

Common factors effectively capture cross-market commonality, which are also informative for the aggregate economy. The factors account for substantial variation in asset returns both in-sample and out-of-sample, while the presence of mispricing is exploited to construct an "arbitrage" portfolio. A joint MVE portfolio is built on large cross-sectional individual assets, of which a high Sharpe ratio results from bilateral hedging among different asset classes. Common factors can also be used as the benchmark basis payoff to gauge the extent of market segmentation, revealing significant segmentation for all market pairs.

Our results shall benefit future research and inspire some promising directions. Our common factors, pairwise factors, and single-asset-class factors, explaining substantial return variation across, between and within asset classes, provide additional sources of useful factors for future studies. The novel approach to construct MVE portfolios can be applied to other asset classes, particularly commonly presented unbalanced panels. In particular, our newly developed framework to measure market segmentation is applicable to broader contexts, such as international financial markets. Moreover, the empirical findings of significant market

segmentation also challenge the assumption of integrated asset markets, which are commonly used in the literature. All of these studies are expected to be conducted in the near future.

Appendix: Additional Proofs

We provide the additional proofs in the main paper.

Proof 1. We assume that the idiosyncratic errors in the model of (2.5) or (2.3) are homoskedastic and uncorrelated across/within different asset classes, i.e. $\text{Var}_t(\boldsymbol{\xi}_{t+1}) = \sigma_t^2 \boldsymbol{I}$. Then the problem in (6.1) across/within markets can be expressed as

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

where $\tilde{\boldsymbol{R}}_{t+1} = (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \boldsymbol{Z}_t' \boldsymbol{R}_{t+1}$. The first order condition with respect to $\boldsymbol{w}_t$ is:

$$\boldsymbol{Z}_t E_t[\tilde{\boldsymbol{R}}_{t+1}] - \boldsymbol{Z}_t \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' \boldsymbol{w}_t - \sigma_t^2 \boldsymbol{w}_t = 0,$$

Then it follows

$$\left[\boldsymbol{Z}_t \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' + \sigma_t^2 \boldsymbol{I} \right] \boldsymbol{w}_t = \boldsymbol{Z}_t E_t[\tilde{\boldsymbol{R}}_{t+1}].$$

Hence, the unique solution for $\boldsymbol{w}_t$ is:

$$\boldsymbol{w}_t = \left[\boldsymbol{Z}_t \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' + \sigma_t^2 \boldsymbol{I} \right]^{-1} \boldsymbol{Z}_t E_t[\tilde{\boldsymbol{R}}_{t+1}].$$

We apply Sherman–Morrison-Woodbury formula and get:

$$\left[\boldsymbol{Z}_t \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' + \sigma_t^2 \boldsymbol{I} \right]^{-1} = \frac{1}{\sigma_t^2} \left[\boldsymbol{I} - \boldsymbol{Z}_t \left(\sigma_t^2 \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} + \boldsymbol{Z}_t' \boldsymbol{Z}_t \right)^{-1} \boldsymbol{Z}_t' \right].$$

Now, the optimal weight is:

$$\boldsymbol{w}_t = \frac{1}{\sigma_t^2} \boldsymbol{Z}_t \left[\boldsymbol{I} - \boldsymbol{Z}_t \left(\sigma_t^2 \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} + \boldsymbol{Z}_t' \boldsymbol{Z}_t \right)^{-1} \boldsymbol{Z}_t' \boldsymbol{Z}_t \right] E_t[\tilde{\boldsymbol{R}}_{t+1}].$$

Next, notice the matrix identity $\boldsymbol{I} - (\mathbf{X} + \mathbf{Y})^{-1} \mathbf{Y} = (\mathbf{X} + \mathbf{Y})^{-1} \mathbf{X}$ with $\mathbf{X} = \sigma_t^2 \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1}$ and $\mathbf{Y} = \boldsymbol{Z}_t' \boldsymbol{Z}_t$, it follows

$$\boldsymbol{w}_t = \boldsymbol{Z}_t \left[\sigma_t^2 \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} + \boldsymbol{Z}_t' \boldsymbol{Z}_t \right]^{-1} \text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} E_t[\tilde{\boldsymbol{R}}_{t+1}].$$

Notice that

$$\left[\sigma_t^2 \,\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} + \boldsymbol{Z}_t' \boldsymbol{Z}_t \right]^{-1} \text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}]^{-1} = \left[\sigma_t^2 \boldsymbol{I} + \text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' \boldsymbol{Z}_t \right]^{-1}.$$

Lastly, we have

$$\begin{aligned} \boldsymbol{w}_t &= \boldsymbol{Z}_t (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} (\boldsymbol{Z}_t' \boldsymbol{Z}_t) \left[\sigma_t^2 \boldsymbol{I} + \text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] \boldsymbol{Z}_t' \boldsymbol{Z}_t \right]^{-1} E_t[\tilde{\boldsymbol{R}}_{t+1}], \\ &= \boldsymbol{Z}_t (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \left[\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] + \sigma_t^2 (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \right]^{-1} E_t[\tilde{\boldsymbol{R}}_{t+1}]. \end{aligned}$$

Let $\tilde{\boldsymbol{b}}_t = \left[\text{Var}_t[\tilde{\boldsymbol{R}}_{t+1}] + \sigma_t^2 (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \right]^{-1} E_t[\tilde{\boldsymbol{R}}_{t+1}]$, then $\boldsymbol{w}_t = \boldsymbol{Z}_t (\boldsymbol{Z}_t' \boldsymbol{Z}_t)^{-1} \tilde{\boldsymbol{b}}_t$.

Lastly, following Hansen and Jagannathan (1997), if LOP holds across or within markets,

the associated SDF is given by $M_{t+1} = 1 - w_t' \left(R_{t+1} - E_t\left[R_{t+1}\right]\right)$. Equivalently, $M_{t+1} = 1 - \tilde{b}_t' \left(\tilde{R}_{t+1} - E_t[\tilde{R}_{t+1}]\right)$.

Proof 2. Denote return space expanded by the common factors $\boldsymbol{F}^C$ as $\mathcal{F}^C$ and the return space expanded by ξ^X as $\boldsymbol{\xi}^X$ for $X \in \{s, b, o\}$. The model specification in (2.4) implies that the return space $\mathcal{R}^X = \mathcal{F}^C \bigcup \boldsymbol{\xi}^X$ since characteristics are predetermined. Hence, for two markets $A, B \in \{s, b, o\}$, we have

$$\begin{aligned}\mathcal{R}^A \bigcap \mathcal{R}^B &= (\mathcal{F}^C \bigcup \boldsymbol{\xi}^A) \bigcap (\mathcal{F}^C \bigcup \boldsymbol{\xi}^B) \\ &= \left(\mathcal{F}^C \bigcup (\boldsymbol{\xi}^A \bigcap \mathcal{F}^C)\right) \bigcup \left((\mathcal{F}^C \bigcap \boldsymbol{\xi}^B) \bigcup (\boldsymbol{\xi}^A \bigcap \boldsymbol{\xi}^B)\right).\end{aligned}$$

If the basis of spaces $\mathcal{F}^C$ and $\boldsymbol{\xi}^X$ are orthogonal to each other, i.e., $\boldsymbol{F}^C \perp \xi^A \perp \xi^B$, then $\boldsymbol{\xi}^A \bigcap \mathcal{F}^C = \mathcal{F}^C \bigcap \boldsymbol{\xi}^B = \boldsymbol{\xi}^A \bigcap \boldsymbol{\xi}^B = \varnothing$. It follows $\mathcal{F}^C = \mathcal{R}^A \bigcap \mathcal{R}^B$. Moreover, under $\boldsymbol{F}^C \perp \xi^A \perp \xi^B$, the specification in (2.4) also implies that $\mathcal{F}^C = \widetilde{\mathcal{R}}^A \bigcap \widetilde{\mathcal{R}}^B$. Similarly, we can prove the results on three markets: $\mathcal{F}^C = \mathcal{R}^s \bigcap \mathcal{R}^b \bigcap \mathcal{R}^o = \widetilde{\mathcal{R}}^s \bigcap \widetilde{\mathcal{R}}^b \bigcap \widetilde{\mathcal{R}}^o$.

Proof 3. For any $M^X \in \mathcal{M}^X$ and $\tilde{R}^X \in \widetilde{\mathcal{R}}^X$ in market $X \in \{A, B\}$, because $\widetilde{\mathcal{R}}^X \subseteq \mathcal{R}^X$, we have $E[M_t^X \tilde{R}_t^X] = 0$ at any time t. It follows $\mathcal{M}^X \subseteq \widetilde{\mathcal{M}}^X$. Hence, we have

$$d(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B) = \min_{\tilde{m}^A \in \widetilde{\mathcal{M}}^A,\, \tilde{m}^B \in \widetilde{\mathcal{M}}^B} \|\tilde{m}^A - \tilde{m}^B\|^2 \leqslant \min_{m^A \in \mathcal{M}^A,\, m^B \in \mathcal{M}^B} \|m^A - m^B\|^2 = d(\mathcal{M}^A, \mathcal{M}^B).$$

Moreover, if expected returns are fully captured by characteristics, i.e., $E_t[R_{t+1}^X] = Z_t^{X\prime} E_t[\tilde{R}_{t+1}^X]$, then $R_{t+1}^X = Z_t^{X\prime} \tilde{R}_{t+1}^X + \xi_{t+1}^X$ with $E_t[\xi_{t+1}^X] = 0$ for market $X \in \{A, B\}$. Then any $\tilde{M}^X \in \widetilde{\mathcal{M}}^X$ and $R^X \in \mathcal{R}^X$, we have

$$E_t[\tilde{M}_{t+1}^X R_{t+1}^X] = Z_t^{X\prime} E_t[\tilde{M}_{t+1}^X \tilde{R}_{t+1}] + E_t[\tilde{M}_{t+1}^X \xi_{t+1}^X].$$

If ξ^X is independent to $\tilde{R}^X$, then $E_t[\tilde{M}_{t+1}^X R_{t+1}^X] = E_t[\tilde{M}_{t+1}^X \xi_{t+1}^X] = 0$. It follows $\widetilde{\mathcal{M}}^X \subseteq \mathcal{M}^X$. Hence, we have $\widetilde{\mathcal{M}}^X = \mathcal{M}^X$, $d(\widetilde{\mathcal{M}}^A, \widetilde{\mathcal{M}}^B) = d(\mathcal{M}^A, \mathcal{M}^B)$.

Proof 4. Suppose $\{\breve{M}_t^{A,B} f_t\}$ is a stationary ergodic process. Under mild regular conditions in Chapter 5 of White (2001),

$$\hat{V} \to_p V, \quad \frac{1}{T}\sum_{t=1}^{T} f_t f_t' \to_p E[f_t f_t'], \quad \text{and} \quad \frac{1}{\sqrt{T}}\sum_{t=1}^{T} \breve{M}_t^{A,B} f_t \to_d N(0, V).$$

It is easy to derive that

$$T\hat{d}(\mathcal{M}^A, \mathcal{M}^B) = \left[\hat{V}^{-1/2}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T} \breve{M}_t^{A,B} f_t\right)\right]' \left[\hat{V}^{1/2}\left(\frac{1}{T}\sum_{t=1}^{T} f_t f_t'\right)^{-1} \hat{V}^{1/2}\right] \left[\hat{V}^{-1/2}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T} \breve{M}_t^{A,B} f_t\right)\right].$$

Since there exists an orthogonal matrix H such that $Q = \hat{V}^{1/2}\left(\frac{1}{T}\sum_{t=1}^{T} f_t f_t'\right)^{-1}\hat{V}^{1/2} = H\Lambda H$, where Λ is a diagonal matrix of the eigenvalues of Q, (7.5) follows.

Proof 5. Consider the two linear regression for $X \in \{A, B\}$

$$\widehat{f}_t^C = \delta_A^C + \Gamma_A^C \tilde{R}_t^A + \varepsilon_t^{Af},\ \widehat{f}_t^C = \delta_B^C + \Gamma_B^C \tilde{R}_t^B + \varepsilon_t^{Bf}.$$

We define

$$\mathcal{Y} = \begin{bmatrix} \hat{\boldsymbol{F}}^{\boldsymbol{C}} \\ \hat{\boldsymbol{F}}^{\boldsymbol{C}} \end{bmatrix}, \quad \mathcal{X} = \begin{bmatrix} \tilde{\boldsymbol{R}}^A & 0 \\ 0 & \tilde{\boldsymbol{R}}^B \end{bmatrix}, \quad \mathcal{E} = \begin{bmatrix} \boldsymbol{\varepsilon}^{Af} \\ \boldsymbol{\varepsilon}^{Bf} \end{bmatrix}, \quad \Lambda = \begin{bmatrix} \Lambda_A \\ \Lambda_B \end{bmatrix},$$

where $\hat{\boldsymbol{F}}^{\boldsymbol{C}} = [\widehat{f}_1^{C\prime}, ..., \widehat{f}_T^{C\prime}]'$, $\tilde{\boldsymbol{R}}^X = [\tilde{R}_1^{X\prime}, ..., \tilde{R}_T^{X\prime}]'$, $\boldsymbol{\varepsilon}^{Xf} = [\varepsilon_1^{Xf\prime}, ..., \varepsilon_T^{Xf\prime}]'$, and $\Lambda_X = [\delta_X^C,\ \Gamma_X^C]'$ for $X \in \{A, B\}$. Then the equation system can be written compactly as $\mathcal{Y} = \mathcal{X}\Lambda + \mathcal{E}$ with OLS estimator $\hat{\Lambda} = (\mathcal{X}'\mathcal{X})^{-1}\mathcal{X}'\mathcal{Y}$. Let $\hat{Q}_{\mathcal{X}\mathcal{X}} = \mathcal{X}'\mathcal{X}$ and $\hat{\Sigma} = \mathcal{X}'\mathcal{E}$, then

$$\text{vec}(\hat{\Lambda}) - \text{vec}(\Lambda) = (I_K \otimes \hat{Q}_{\mathcal{X}\mathcal{X}})\,\text{vec}(\hat{\Sigma}),$$

where we use the property: $\text{vec}\left(\hat{Q}_{\mathcal{X}\mathcal{X}}\hat{\Sigma}I_K'\right) = (I_K \otimes \hat{Q}_{\mathcal{X}\mathcal{X}})\,\text{vec}(\hat{\Sigma})$. Under some mild conditions, we have

$$\sqrt{T}\big(\,\text{vec}(\hat{\Lambda}) - \text{vec}(\Lambda)\big) \xrightarrow{d} \mathcal{N}\left(0, (I_K \otimes Q_{\mathcal{X}\mathcal{X}}^{-1})\,\Omega\,(I_K \otimes Q_{\mathcal{X}\mathcal{X}}^{-1})\right),$$

where $\hat{Q}_{\mathcal{X}\mathcal{X}} \to_p Q_{\mathcal{X}\mathcal{X}}$ and $\Omega = \text{Var}[\text{vec}(\hat{\Sigma})]$.

Define the selection vector $L = I_K \otimes \ell'$ with $\ell = [1, 0 \ldots 0, -1, 0 \ldots 0]'$ such that $\delta_A^C - \delta_B^C = L\,\text{vec}(\Lambda)$. Then we have

$$\sqrt{T}(\hat{\delta}_A^C - \hat{\delta}_B^C - (\delta_A^C - \delta_B^C)) \longrightarrow_d \mathcal{N}\left(0, L\left(I_K \otimes Q_{\mathcal{X}\mathcal{X}}^{-1}\right)\Omega\left(I_K \otimes Q_{\mathcal{X}\mathcal{X}}^{-1}\right)L'\right).$$

Under the null hypothesis $H_0 : \delta_A^C - \delta_B^C = 0$, a Wald test statistic is given by

$$W = T\,(\hat{\delta}_A^C - \hat{\delta}_B^C)'\hat{V}_{AB}^{-1}(\hat{\delta}_A^C - \hat{\delta}_B^C) \longrightarrow_d \chi^2(K).$$

with $\hat{V}_{AB} = L\left(I_K \otimes \hat{Q}_{\mathcal{X}\mathcal{X}}^{-1}\right)\widehat{\Omega}\left(I_K \otimes \hat{Q}_{\mathcal{X}\mathcal{X}}^{-1}\right)L'$.

Proof 6. The common factors extracted based regressed-PCA is $\hat{f}_t^{AB} = B_{ca}\tilde{R}_t^A + B_{cb}\tilde{R}_t^B$. Then if $E[\tilde{M}_t^A\tilde{R}_t^B] = 0$, we can obtain $E[\tilde{M}_t^A\hat{f}_t^{AB}] = B_{cb}E[\tilde{M}_t^A\tilde{R}_t^B] = 0$. However, $E[\tilde{M}_t^A\hat{f}_t^{AB}] = B_{cb}E[\tilde{M}_t^A\tilde{R}_t^B] = 0$ does not imply $E[\tilde{M}_t^A\tilde{R}_t^B] = 0$. The same analysis applies on $E[\tilde{M}_t^B\tilde{R}_t^A]$.

Meanwhile, it is easy to get $E[\tilde{M}_t^A\hat{f}_t^{AB}] - E[\tilde{M}_t^B\hat{f}_t^{AB}] = B_{cb}E[\tilde{M}_t^A\tilde{R}_t^B] - B_{ca}E[\tilde{M}_t^B\tilde{R}_t^A]$. Since $B_{ca} \neq 0$ and $B_{cb} \neq 0$, we can conclude that $E[\tilde{M}_t^A\hat{f}_t^{AB}] - E[\tilde{M}_t^B\hat{f}_t^{AB}] = 0$ is not equivalent to $E[\tilde{M}_t^A\tilde{R}_t^B] - E[\tilde{M}_t^B\tilde{R}_t^A] = 0$.

Appendix: Figures and Tables

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	734,255	8,025	2,987	0.90%	17.45%	-14.41%	-6.10%	0.30%	6.64%	15.24%
CorpBond	196,807	904	386	0.41%	3.53%	-1.68%	-0.40%	0.25%	1.19%	2.81%
Option	759,380	5,042	1,720	-0.70%	6.92%	-6.46%	-3.48%	-1.29%	1.23%	5.73%

[†] 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 returns, the standard deviation, and $10th$, $25th$, $50th$. $75th$ and $90th$ percentiles of the return distribution, respectively.

Figure 1: Cumulative returns of the first five common factors (F^C)

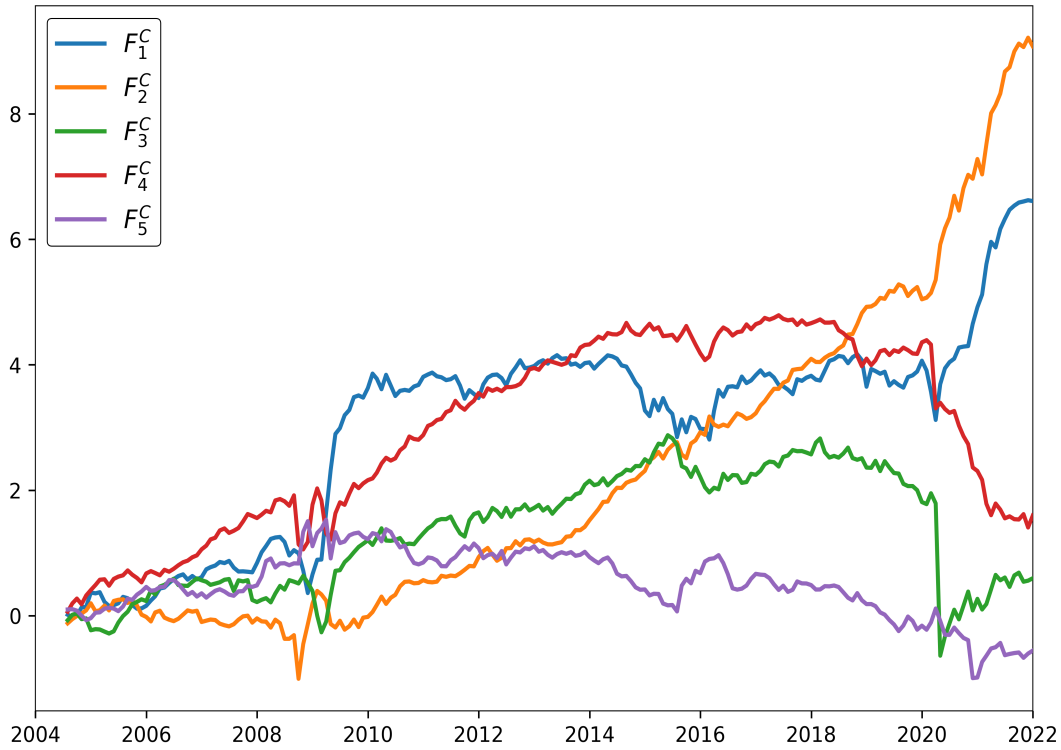


Table 2: Correlations between common factors and observable factors[†]

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
$MKTstock$	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***

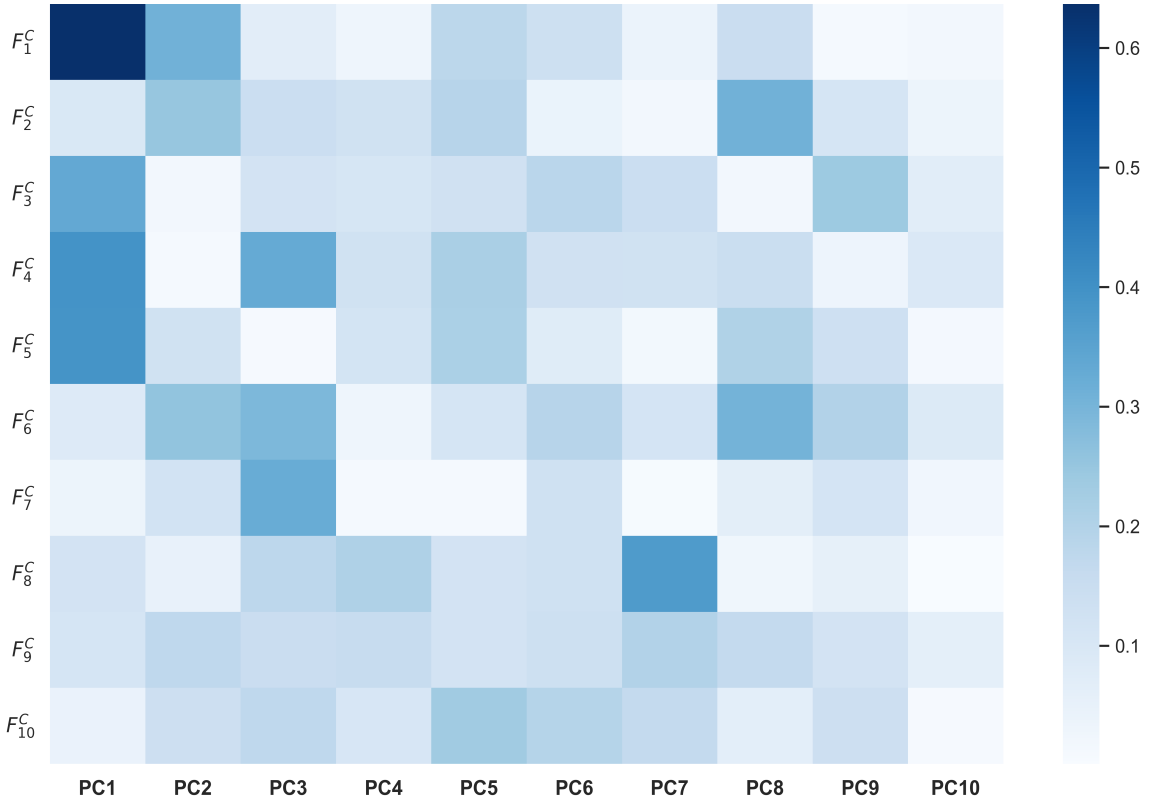
[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. The observable factors include six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $BONDMOM$, $REV*$, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$). See Appendix A2 for details on these observable factors.

Table 3: Regression of common factors on observable factors[†]

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
(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

[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. The observable factors include 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.

Figure 2: Common factors (F^C) *vs.* principal components (PC) of observable factors (top panel: correlations; bottom panel: plots)



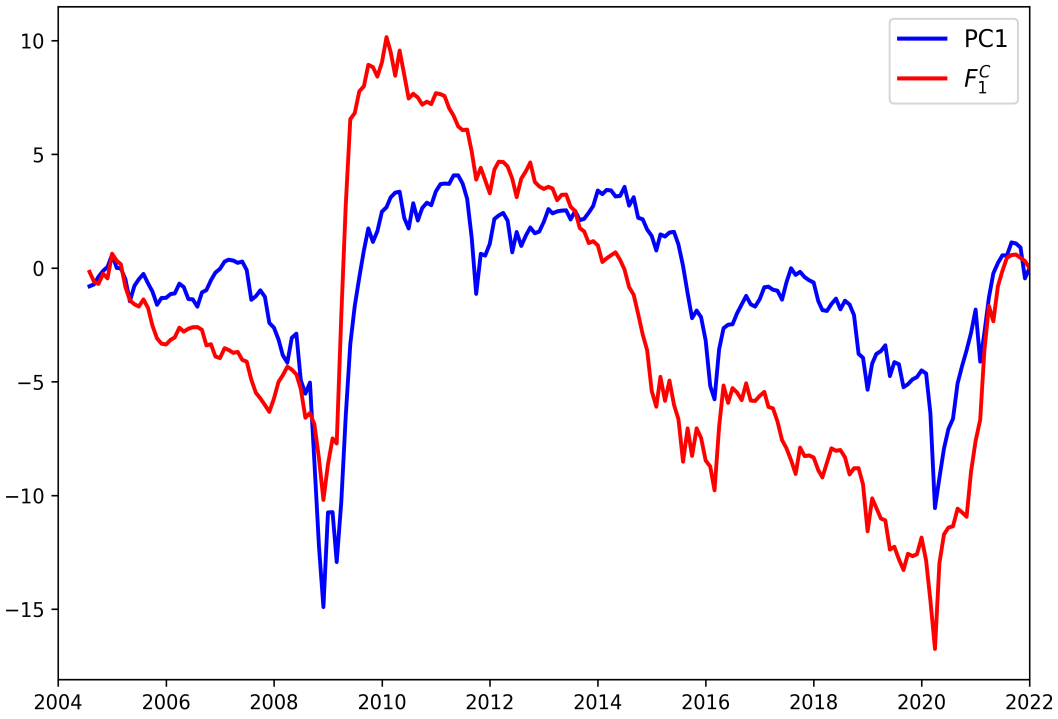


Table 4: Correlations between common and single-asset-class factors†

Factors	F_1^s	F_2^s	F_3^s	F_4^s	F_5^s	F_6^s	F_7^s	F_8^s	F_9^s	F_{10}^s
F_1^C	0.85***	0.08	0.12*	-0.14**	0.21***	0.19***	0.01	0.03	0.01	0.03
F_2^C	-0.09	0.04	-0.02	-0.07	0.11	-0.13*	-0.10	-0.07	-0.04	-0.04
F_3^C	-0.46***	0.37***	0.38***	-0.14**	0.24***	0.27***	-0.01	0.05	-0.00	0.03
F_4^C	-0.02	0.42***	-0.43***	-0.21***	0.15**	0.18***	0.09	0.05	-0.00	0.13*
F_5^C	0.20***	0.69***	0.13*	0.27***	-0.32***	-0.34***	-0.07	0.01	-0.10	-0.04
F_6^C	0.05	-0.35***	0.24***	0.04	-0.27***	0.05	0.22***	0.04	-0.08	0.09
F_7^C	-0.01	0.22***	0.15**	-0.14**	-0.36***	0.15**	0.28***	-0.08	0.11	0.02
F_8^C	0.03	-0.06	0.63***	0.01	0.24***	-0.17**	-0.04	0.04	-0.05	0.08
F_9^C	0.00	0.00	-0.17**	0.78***	0.16**	0.30***	0.05	0.05	-0.01	-0.04
F_{10}^C	0.01	-0.11	-0.26***	-0.28***	-0.16**	-0.17**	-0.09	0.23***	-0.13*	0.01
Factors	F_1^b	F_2^b	F_3^b	F_4^b	F_5^b	F_6^b	F_7^b	F_8^b	F_9^b	F_{10}^b
F_1^C	0.62***	0.32***	0.24***	0.00	0.06	0.14**	0.04	-0.11	0.07	0.10
F_2^C	-0.53***	0.30***	0.02	-0.04	0.11	-0.00	0.12*	-0.11*	0.01	0.09
F_3^C	0.51***	0.09	-0.28***	0.01	0.09	-0.19***	0.14**	0.05	-0.18***	-0.00
F_4^C	-0.15**	0.61***	0.31***	0.20***	-0.01	0.05	0.06	0.01	-0.11	-0.09
F_5^C	-0.11*	-0.07	-0.47***	-0.00	-0.06	0.02	0.24***	0.14*	0.07	-0.10
F_6^C	-0.05	0.39***	-0.38***	-0.25***	0.07	-0.26***	0.02	-0.07	0.26***	0.26***
F_7^C	-0.04	-0.37***	0.55***	-0.22***	0.12*	-0.28***	0.28***	0.03	0.15**	0.15**
F_8^C	-0.09	-0.03	0.13*	0.24***	0.03	-0.05	-0.20***	-0.02	-0.10	0.12*
F_9^C	0.01	-0.16**	-0.03	0.11	-0.16**	-0.09	-0.26***	-0.19***	0.01	0.02
F_{10}^C	0.06	-0.27***	-0.14**	0.51***	0.14**	0.06	0.13*	-0.20***	0.20***	0.13*
Factors	F_1^o	F_2^o	F_3^o	F_4^o	F_5^o	F_6^o	F_7^o	F_8^o	F_9^o	F_{10}^o
F_1^C	0.44***	0.14**	0.07	-0.23***	0.05	0.19***	-0.08	-0.14**	-0.09	0.06
F_2^C	0.80***	0.05	0.05	0.16**	0.01	-0.06	0.02	0.02	0.03	-0.05
F_3^C	0.24***	0.25***	0.08	-0.12*	-0.19***	-0.07	-0.06	0.13*	-0.01	0.10
F_4^C	-0.27***	0.49***	0.46***	-0.22***	-0.07	0.05	-0.04	-0.06	0.04	0.04
F_5^C	-0.06	-0.03	-0.08	0.49***	-0.17**	0.05	0.12*	-0.03	-0.03	0.02
F_6^C	-0.10	0.61***	-0.48***	0.14**	-0.02	0.05	-0.05	0.10	-0.05	-0.09
F_7^C	0.04	0.31***	-0.33***	-0.02	0.10	-0.01	0.05	-0.09	0.10	-0.05
F_8^C	-0.08	0.12*	0.42***	0.35***	0.39***	0.03	-0.11*	-0.03	-0.08	0.00
F_9^C	0.06	0.25***	0.08	-0.08	0.27***	-0.20***	0.06	-0.00	0.05	-0.04
F_{10}^C	0.06	0.29***	0.17**	0.25***	-0.12*	0.05	0.15**	0.02	0.12*	-0.08

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. F^C denotes common factors; F^X for $X \in \{s, b, o\}$ denotes single-asset-class regressed-PCA factors for stock, corporate bond, and option markets, respectively.

Figure 3: Estimates of coefficients B for the first common factor with 95% confidence intervals

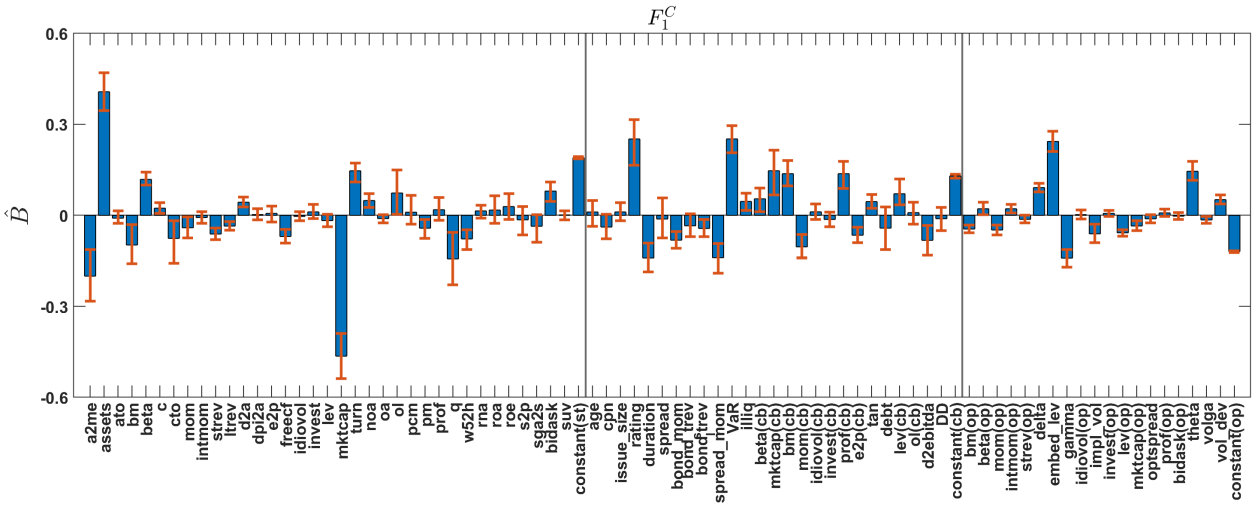


Table 5: Contribution of asset-class-specific constituents to the common factors†

	F_s^C	F_b^C	F_o^C
F_1^C	0.89	0.74	0.51
	[0.57]	[0.29]	[0.14]
F_2^C	0.25	0.61	0.81
	[0.03]	[0.33]	[0.64]
F_3^C	0.71	0.60	0.40
	[0.52]	[0.36]	[0.13]
F_4^C	0.67	0.72	0.70
	[0.29]	[0.37]	[0.35]
F_5^C	0.84	0.53	0.53
	[0.67]	[0.21]	[0.12]
F_6^C	0.54	0.66	0.78
	[0.23]	[0.32]	[0.45]
F_7^C	0.56	0.76	0.47
	[0.24]	[0.57]	[0.20]
F_8^C	0.72	0.33	0.66
	[0.54]	[0.11]	[0.36]
F_9^C	0.88	0.35	0.41
	[0.70]	[0.11]	[0.19]
F_{10}^C	0.52	0.62	0.44
	[0.30]	[0.45]	[0.25]

† For each common factor, the first row shows its correlations with associated asset-class-specific constituents; the second row shows its variance decomposition in square brackets, defined as $\frac{\text{Cov}(F_X^C, F^C)}{\text{Var}(F^C)}$ for $X \in \{s, b, o\}$.

Table 6: Correlations between common factors and macroeconomic and financial variables[†]

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
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
ΔIP	-0.22***	-0.17**	0.40***	0.03	0.05	-0.03	-0.21***	0.05	-0.15**	-0.01
$\Delta(FFR)$	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
$\Delta(EPU)$	-0.16**	0.08	-0.36***	-0.17**	0.13*	0.05	0.17**	-0.14**	0.03	0.12*
$\Delta(FINU)$	-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

[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. See Section 4.2 for details on the macroeconomic and financial variables.

Table 7: Regression of common factors on macroeconomic and financial variables[†]

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
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]
ΔIP	-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]
$\Delta(FFR)$	-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]
$\Delta(EPU)$	-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]
$\Delta(FINU)$	-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%

[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. The Shapley-Owen R^2's are in square brackets. Common factors, macroeconomic and financial variables are standardized using the time-series standard deviation. See Section 4.2 for details on macroeconomic and financial variables.

Table 8: Regression for the asset-class-specific components of the first common factor on macroeconomic and financial variables[†]

	$\widehat{F}_s^C$	$\widehat{F}_b^C$	$\widehat{F}_o^C$
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)
ΔIP	-0.30***	-0.15*	-0.29**
	(-2.74)	(-1.86)	(-2.48)
$\Delta(FFR)$	-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)
$\Delta(EPU)$	0.03	-0.16**	0.04
	(0.44)	(-2.35)	(0.45)
$\Delta(FINU)$	-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%

[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. Common factors, macroeconomic and financial variables are standardized using the time-series standard deviation See Section 4.2 for details on macroeconomic and financial variables.

Table 9: Forecasting and nowcasting of macro-financial variables with ten common factors

	Panel I: Forecast			Panel II: Nowcast		
	β^Y	t	R^2 (%)	β^Y	t	R^2 (%)
Core inflation	1.91***	(6.35)	21.42	0.54*	(1.88)	2.32
$\Delta(FFR)$	0.23**	(2.48)	3.99	0.38***	(4.03)	9.84
Δc	0.88**	(2.11)	2.91	-0.09	(-0.28)	0.05
$\Delta INDPRO$	0.40*	(1.89)	2.35	-0.00	(-0.01)	0.00
$\Delta(MACU)$	0.05	(1.06)	0.75	0.07	(1.15)	0.88
$\Delta(DEF)$	0.09	(0.98)	0.65	-0.12	(-1.59)	1.67
$\Delta(TERM)$	0.12	(0.89)	0.53	0.50***	(4.42)	11.61
$\Delta(FINU)$	0.02	(0.42)	0.12	0.52***	(5.66)	17.69
LIQ	-0.02	(-0.16)	0.02	-0.01	(-0.19)	0.02
$\Delta(VIX)$	-0.12	(-0.65)	0.29	0.17***	(4.38)	11.41
$\Delta(EPU)$	-0.08	(-1.24)	1.03	-0.03	(-0.30)	0.06
HKM	-0.25*	(-1.84)	2.24	0.84***	(11.05)	45.03

[†] Panel I and II tabulate the forecasting and nowcasting regression coefficients in Section 4.2.2, respectively.

Table 10: Sharpe ratios of the common and asset-class-specific factors[†]

I: Common factors										
	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**
- Stocks	**0.49**	-0.40	-0.31	-0.05	0.30	0.14	0.05	0.37	0.31	-0.26
- Corp Bond	0.23	0.19	0.01	**0.57**	-0.26	0.19	-0.05	0.13	**-0.72**	-0.11
- Option	**1.57**	**1.50**	**2.01**	0.32	-0.15	**1.54**	**1.94**	**1.17**	**2.61**	**2.63**
Out of sample	0.49	**2.51**	0.01	0.59	-0.25	0.09	-0.48	0.16	-0.08	-0.31
- Stocks	0.12	0.08	-0.05	-0.52	-0.37	0.11	0.11	-0.22	**-0.77**	0.13
- Corp Bond	-0.24	**1.01**	-0.32	-0.52	-0.20	**0.72**	-0.59	-0.13	-0.04	-0.20
- Option	**2.39**	**2.87**	0.37	**1.84**	0.37	-0.40	-0.45	0.43	0.43	-0.38

II: Stock factors										
	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	0.11	-0.32	-0.13	-0.14	0.22	0.29	0.12	-0.23	-0.06	-0.28

III: Corporate bond factors										
	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	**-0.73**	**0.76**	-0.48	-0.07	**1.03**	0.14	**-0.54**	0.37	**-0.80**	**0.76**

IV: Option factors										
	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	**2.78**	-0.42	-0.32	**0.90**	0.40	0.35	**0.94**	**0.74**	-0.20	**1.13**

[†] Panel I reports the in-sample and out-of-sample annualized Sharpe ratios of common factors and their asset-class-specific components. Panel I-IV report the annualized Sharpe ratios of the asset-class-specific factors.

Table 11: In-sample and out-of-sample performance (R^2) of the common factors[†]

I: All asset returns

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	2.81	4.92	4.34
2	25.15	7.27	3.58	8.69	5.51
3	32.91	8.88	3.98	12.21	6.19
4	40.16	11.46	4.14	11.54	6.43
5	46.02	13.34	4.42	11.19	6.74
6	52.12	14.26	4.72	10.89	7.12
7	56.59	14.76	4.86	9.74	7.31
8	60.40	15.51	5.08	12.19	7.66
9	63.87	16.31	5.27	12.99	7.95
10	67.01	16.76	5.42	12.85	8.15
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.20	0.39	0.35	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	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.22	0.62	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	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	2.22	1.67	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	1.19	5.20	2.31
2	29.73	7.66	2.07	9.12	4.07
3	33.15	9.97	2.32	12.68	4.64
4	41.88	13.76	2.45	11.99	4.86
5	44.07	15.35	2.75	11.65	5.05
6	54.30	16.76	2.88	11.22	5.12
7	57.40	17.26	2.95	10.01	5.15
8	62.69	17.81	3.20	12.55	5.61
9	65.20	19.00	3.34	13.34	5.83
10	67.97	19.53	3.49	13.19	6.07
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.14	0.37	0.51	27.80	

[†]K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table 12: Out-of-sample performance of the pure-*alpha* strategy[†]

I: Pure-*alpha* portfolios

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 components

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 components

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 components

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

[†]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* portfolios and their associated components in (5.6).

Figure 4: Estimates of coefficients a with 95% confidence intervals ($K = 10$)

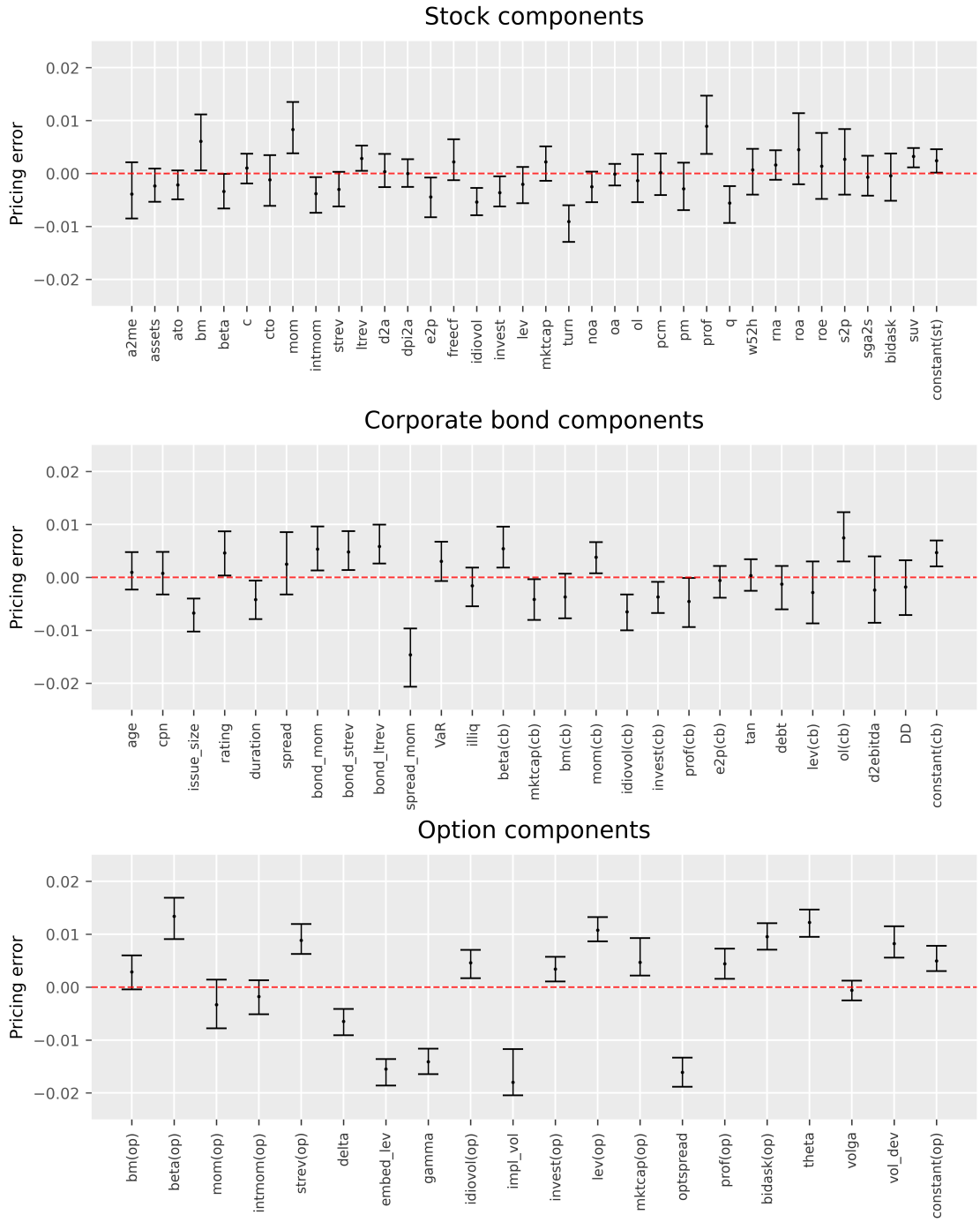


Table 13: In-sample Sharpe ratios of MVE portfolio and its constituents and their correlations with common factors†

I: Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE/constituents	4.22	2.08	1.05	2.81
Mean	5.26	1.54	0.54	3.18
Std	4.32	2.56	1.79	3.93
Single-market MVE	-	2.98	1.58	2.64
Mean	-	6.39	2.07	6.68
Std	-	7.42	4.55	8.78

II: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.50***	0.03	0.76***
Stock	-	-	-0.16**	-0.03
CorpBond	-	-	-	-0.32***

III: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	-0.09	-0.30***	0.36***	-0.08
F_2^C	0.07	-0.18***	0.00	0.19***
F_3^C	-0.04	-0.09	0.07	-0.02
F_4^C	-0.04	0.07	0.38***	-0.26***
F_5^C	-0.02	-0.01	-0.23***	0.09
F_6^C	-0.02	0.03	-0.11	0.00
F_7^C	-0.07	-0.05	-0.07	-0.01
F_8^C	-0.08	-0.09	0.11	-0.08
F_9^C	0.15**	0.13*	-0.04	0.10
F_{10}^C	0.10	0.12*	0.04	0.01

† The joint MVE portfolio is constructed with $K = 10$, where its constituents is defined in (6.5). Panel I shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the single-asset-class MVE portfolios. Panel II reports correlations among the constituents in the joint MVE portfolio. Panel III reports correlations between the constituents of the joint MVE portfolio and the common factors.

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

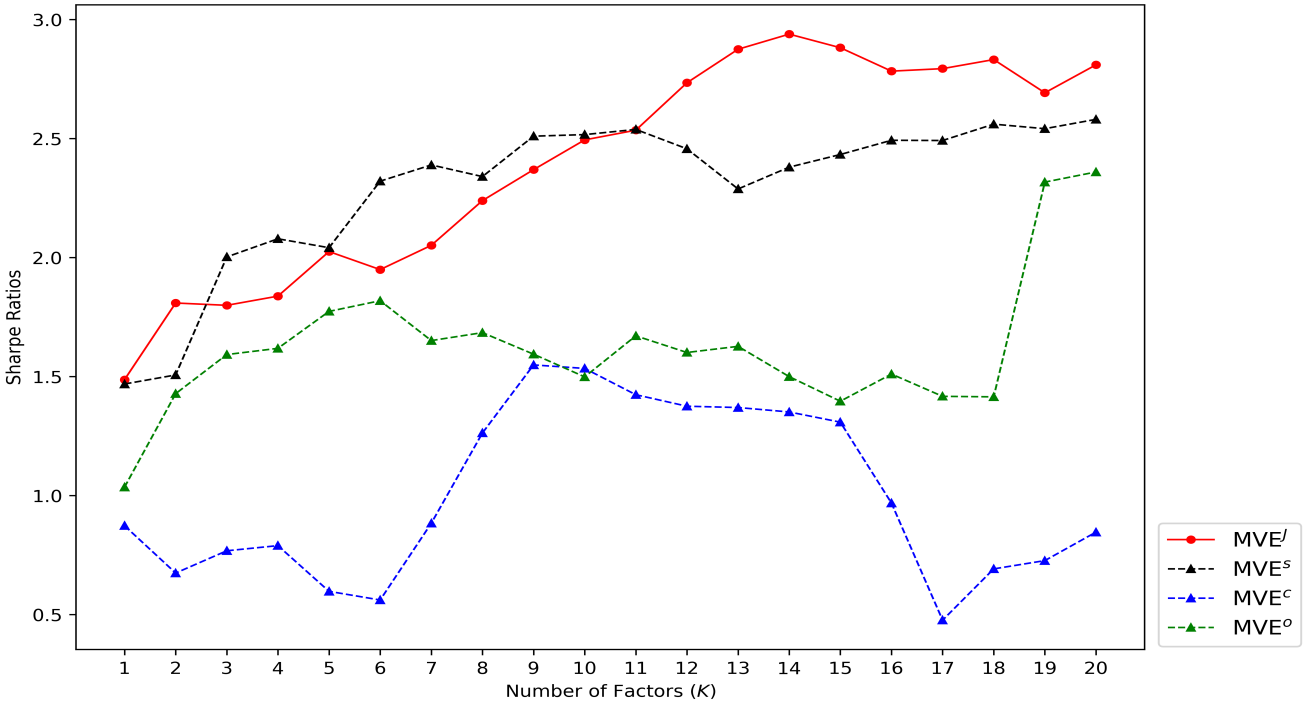


Table 14: Market distances based on common and pairwise factors[†]

K	$\hat{d}(\mathcal{M}^s,\mathcal{M}^b)$	p	$\hat{d}(\mathcal{M}^s,\mathcal{M}^o)$	p	$\hat{d}(\mathcal{M}^b,\mathcal{M}^o)$	p	$\hat{d}(\widetilde{\mathcal{M}}^s,\widetilde{\mathcal{M}}^b)$	p	$\hat{d}(\widetilde{\mathcal{M}}^s,\widetilde{\mathcal{M}}^o)$	p	$\hat{d}(\widetilde{\mathcal{M}}^b,\widetilde{\mathcal{M}}^o)$	p
I: Distance based on common factors: $\boldsymbol{F}^C$												
1	0.32	0.47	1.93	0.34	3.82	0.15	2.17	0.22	1.48	0.56	7.25	0.11
2	0.53	0.62	18.86	0.03	24.78	0.01	4.97	0.17	5.35	0.55	20.49	0.05
3	0.97	0.63	35.75	0.01	36.66	0.01	6.65	0.22	33.10	0.07	36.27	0.02
4	1.70	0.58	36.25	0.02	39.09	0.01	7.29	0.33	33.67	0.10	38.69	0.03
5	2.00	0.63	37.14	0.02	41.31	0.01	7.67	0.42	33.89	0.16	39.88	0.05
6	2.00	0.74	43.85	0.02	48.25	0.01	8.01	0.49	43.74	0.13	53.68	0.02
7	3.53	0.56	45.13	0.03	48.26	0.01	10.64	0.42	51.25	0.15	54.93	0.04
8	4.96	0.43	46.61	0.04	54.09	0.01	15.37	0.28	52.02	0.20	64.26	0.03
9	8.61	0.14	46.99	0.06	60.46	0.01	20.44	0.17	52.10	0.25	70.68	0.03
10	9.50	0.15	49.31	0.07	60.79	0.01	21.87	0.20	54.46	0.28	70.80	0.04
II: Distance based on pairwise factors: F^{sb}, F^{so}, F^{bo}												
1	0.20	0.57	2.55	0.24	23.34	0.01	1.05	0.39	0.29	0.76	28.37	0.02
2	0.47	0.67	31.14	0.02	30.82	0.01	3.70	0.30	20.29	0.12	30.84	0.03
3	1.16	0.59	32.74	0.02	30.82	0.02	4.32	0.43	22.96	0.16	31.13	0.06
4	3.04	0.28	46.42	0.01	42.91	0.01	6.63	0.37	47.97	0.05	43.83	0.03
5	4.06	0.23	46.88	0.01	43.48	0.01	10.28	0.22	48.55	0.07	48.53	0.04
6	4.08	0.34	46.90	0.02	52.93	0.01	10.50	0.31	48.59	0.12	58.68	0.02
7	9.23	0.05	47.98	0.03	81.42	0.00	18.18	0.12	48.64	0.17	95.28	0.00
8	10.73	0.04	60.05	0.01	94.82	0.00	22.21	0.08	58.12	0.14	113.59	0.00
9	12.27	0.04	79.38	0.00	94.83	0.00	27.40	0.08	86.76	0.04	113.62	0.00
10	12.49	0.04	81.48	0.01	95.78	0.00	27.79	0.10	88.76	0.05	118.21	0.00

[†] K denotes the number of factors. $d(\mathcal{M}^A,\mathcal{M}^B)$ for $A,B\in\{s,b,o\}$ denotes the market distances of different pairs based on SDFs constructed as in (7.4); $d(\widetilde{\mathcal{M}}^A,\widetilde{\mathcal{M}}^B)$ for $A,B\in\{s,b,o\}$ denotes the market distances based on the SDFs constructed with managed portfolios. The associated p-values are also reported. The left part of each panel is with SDFs constructed as in (7.4) in the span of individual asset excess returns; the right part is with SDFs in the span of managed portfolio return spaces with $M_{t+1}=1-\boldsymbol{b}_t'(\tilde{R}_{t+1}-E_t[\tilde{R}_{t+1}])$ and $\boldsymbol{b}_t=\mathrm{Var}_t^{-1}[\tilde{\boldsymbol{R}}_{t+1}]E_t[\tilde{\boldsymbol{R}}_{t+1}]$.

Table 15: Market segmentation based on regression approach with common and pairwise factors†

K	δ^C_{s-b}	δ^C_{s-o}	δ^C_{b-o}	δ^{sb}_s	δ^{sb}_b	δ^{sb}_{s-b}	δ^{so}_s	δ^{so}_o	δ^{so}_{s-o}	δ^{bo}_b	δ^{bo}_o	δ^{o}_{b-o}
1	1.84*	-0.88	-2.71	-0.36	1.39	-1.75	2.36***	1.18	1.18	-4.63***	0.92	-5.55***
	(1.67)	(-0.55)	(-1.54)	(-0.66)	(1.61)	(-1.55)	(4.04)	(0.78)	(0.85)	(-5.62)	(1.10)	(-4.76)
2	-0.64	3.84***	4.47***	-0.28	-0.57	0.28	3.89***	-1.19	5.08***	3.35***	1.01	2.34
	(-0.56)	(3.17)	(3.47)	(-0.34)	(-0.97)	(0.33)	(4.08)	(-1.25)	(3.71)	(5.35)	(0.80)	(1.62)
	[0.21]	[0.00]	[0.00]	[0.73]	[0.22]	[0.29]	[0.00]	[0.21]	[0.00]	[0.00]	[0.51]	[0.00]
3	-0.71	-4.62***	-3.92***	-0.19	0.89	-1.08	0.90***	-0.82	1.72	-1.00*	0.09	-1.09
	(-0.78)	(-3.17)	(-3.02)	(-0.46)	(1.18)	(-1.13)	(2.74)	(-0.70)	(1.58)	(-1.72)	(0.11)	(-0.99)
	[0.34]	[0.00]	[0.00]	[0.72]	[0.16]	[0.39]	[0.00]	[0.37]	[0.00]	[0.00]	[0.50]	[0.00]
4	1.24	0.42	-0.82	-0.31	-1.16*	0.85	-4.47***	0.46	-4.93***	1.38***	-1.25	2.64***
	(1.27)	(0.43)	(-0.74)	(-0.68)	(-1.96)	(1.19)	(-6.53)	(1.00)	(-6.21)	(5.28)	(-1.43)	(3.13)
	[0.38]	[0.00]	[0.00]	[0.85]	[0.06]	[0.46]	[0.00]	[0.47]	[0.00]	[0.00]	[0.43]	[0.00]
5	-0.10	0.97	1.07	-0.37	-0.59*	0.22	0.79**	0.80	-0.01	-2.40***	-0.25	-2.15**
	(-0.12)	(0.90)	(1.06)	(-0.45)	(-1.89)	(0.26)	(2.26)	(0.98)	(-0.02)	(-5.41)	(-0.36)	(-2.55)
	[0.51]	[0.00]	[0.00]	[0.73]	[0.08]	[0.54]	[0.00]	[0.59]	[0.00]	[0.00]	[0.34]	[0.00]
6	-0.09	-3.34***	-3.26***	0.12	0.35	-0.23	0.49	0.70	-0.20	4.18***	0.85	3.33***
	(-0.11)	(-3.39)	(-3.62)	(0.30)	(0.58)	(-0.34)	(1.08)	(1.00)	(-0.24)	(8.53)	(1.23)	(4.30)
	[0.63]	[0.00]	[0.00]	[0.51]	[0.07]	[0.65]	[0.00]	[0.72]	[0.00]	[0.00]	[0.41]	[0.00]
7	0.53	1.74	1.22	0.45	-1.39***	1.84***	2.16***	1.24	0.92	-2.43***	1.16*	-3.59***
	(0.80)	(1.59)	(1.15)	(1.22)	(-2.67)	(2.89)	(9.03)	(1.43)	(1.04)	(-6.91)	(1.76)	(-4.33)
	[0.67]	[0.00]	[0.00]	[0.50]	[0.04]	[0.05]	[0.00]	[0.75]	[0.00]	[0.00]	[0.51]	[0.00]
8	1.18	-1.56**	-2.74***	-0.07	-1.17**	1.10*	3.17***	-0.14	3.31***	-2.07***	0.31	-2.38***
	(1.53)	(-1.98)	(-2.77)	(-0.20)	(-2.35)	(1.78)	(7.19)	(-0.24)	(4.66)	(-5.06)	(0.67)	(-3.24)
	[0.51]	[0.00]	[0.00]	[0.49]	[0.07]	[0.05]	[0.00]	[0.43]	[0.00]	[0.00]	[0.16]	[0.00]
9	1.57**	-0.81	-2.38**	0.42	-0.45*	0.86*	0.73**	-1.34**	2.07***	-0.40	0.04	-0.44
	(2.25)	(-0.86)	(-2.43)	(0.85)	(-1.77)	(1.67)	(2.03)	(-2.08)	(2.75)	(-1.58)	(0.05)	(-0.58)
	[0.19]	[0.00]	[0.00]	[0.57]	[0.00]	[0.01]	[0.00]	[0.35]	[0.00]	[0.00]	[0.19]	[0.00]
10	-0.94	-2.46***	-1.53*	0.50	0.21	0.29	-0.90**	-0.05	-0.85	-1.49***	-0.07	-1.42**
	(-1.44)	(-3.22)	(-1.78)	(1.01)	(0.66)	(0.53)	(-2.22)	(-0.12)	(-1.44)	(-3.84)	(-0.21)	(-2.54)
	[0.19]	[0.00]	[0.00]	[0.51]	[0.00]	[0.02]	[0.00]	[0.35]	[0.00]	[0.00]	[0.26]	[0.00]

† K denotes the number of factors. Based on the regressions in (7.7) for $X \in \{A, B\}$ and $A, B \in \{s, b, o\}$, δ^C_X and δ^{AB}_X are reported with t-statistics in parentheses and p-values for GRS-statistics in square brackets; $\delta^C_{A-B} = \delta^C_A - \delta^C_B$ and $\delta^{AB}_{A-B} = \delta^{AB}_A - \delta^{AB}_B$ are reported with t-statistics in parentheses and p-values for statistics of (7.8) in square brackets.

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Appendix A1 Filters and Characteristics

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

Appendix A1.1 Stock

For stocks, we use 35 characteristics that are available from Freyberger, Höppner, Neuhierl, and Weber (2022). For detailed definitions and summary statistics of these characteristics, see Freyberger, Neuhierl, and Weber (2020) and Freyberger, Höppner, Neuhierl, and Weber (2022).

1. **Market beta** (*beta*): Following Frazzini and Pedersen (2014). The CAPM beta is the product of correlations between the excess return of stock i and the market excess return and the ratio of volatilities.

2. **Market capitalization** (*mktcap*): Following Fama and French (1992). The total market capitalization of the previous month is defined as price times shares outstanding.

3. **Book-to-market ratio** (*bm*): Following Fama and French (1992) and Davis, Fama, and French (2000). Ratio of book value of equity to market value of equity.

4. **Gross profitability** (*prof*): Following Ball, Gerakos, Linnainmaa, and Nikolaev (2015). Gross profitability (GP) divided by the book value of equity.

5. **Total assets** (*asset*): Following Gandhi and Lustig (2015). Total assets.

6. **Investment** (*invest*): Following Cooper, Gulen, and Schill (2008). Investment is defined as the percentage year-on-year growth rate in total assets.

7. **Idiosyncratic volatility** (*idiovol*): Following Ang, Hodrick, Xing, and Zhang (2006). Idiosyncratic volatility is the standard deviation of the residuals from a regression of excess returns on the Fama and French (1993) three-factor model.

8. **Book leverage** (*lev*): Following Lewellen (2015). Leverage is the ratio of long-term debt and debt in current liabilities to the sum of long-term debt, debt in current liabilities, and stockholders' equity.

9. **Operating leverage** (ol): Following Novy-Marx (2011). Operating leverage is the sum of cost of goods sold and selling, general, and administrative expenses over total assets.

10. **Momentum** (mom): Following Fama and French (1996). Momentum is the cumulative return from 12 months before the return prediction to two months before.

11. **Intermediate momentum** ($intmom$): Following Novy-Marx (2012). Intermediate momentum is the cumulative return from 12 months before the return prediction to seven months before.

12. **Short-term reversal** ($strev$): Following Jegadeesh (1990). Short-term reversal is the lagged one-month return.

13. **Long-term reversal** ($ltrev$): Following De Bondt and Thaler (1985). Long-term reversal is the cumulative return from 36 months before the return prediction to 13 months before.

14. **Bid-ask spread** ($bidask$): Following Chung and Zhang (2014). The bid-ask spread is the average daily bid-ask spread in the previous month.

15. **Standard unexplained volume** (suv): Following Garfinkel (2009). Standard unexplained volume is the difference between actual volume and predicted volume in the previous month. Predicted volume comes from a regression of daily volume on a constant and the absolute values of positive and negative returns.

16. **Price to 52-week high price** ($w52h$): Following George and Hwang (2004). Closeness to 52-week high is the ratio of stock price at the end of the previous calendar month and the previous 52 week high price.

17. **Total-assets-to-size** ($a2me$): Following Bhandari (1988). The ratio of total assets to the market capitalization as of December $t-1$.

18. **Net operating assets** (noa): Following Hirshleifer, Hou, Teoh, and Zhang (2004). Net operating assets are the difference between operating assets minus operating liabilities scaled by lagged total assets.

19. **Sales-to-lagged-net-operating-assets** (ato): Following Soliman (2008). Net sales over lagged net operating assets.

20. **Sales-to-price** ($s2p$): Following Lewellen (2015). Sales-to-price is the ratio of net sales to the market capitalization as of December.

21. **Cash-to-short-term-investment** (c): Following Palazzo (2012). It is the ratio of cash and short-term investments to total assets.

22. **Capital turnover** (cto): Following Haugen and Baker (1996). Capital turnover is the ratio of net sales to lagged total assets.

23. **Change in property, plants and equipment** ($dpi2a$): Following Lyandres, Sun, and Zhang (2008). It denotes the changes in property, plants, and equipment and inventory over lagged total assets.

24. **Earnings-to-price** ($e2p$): Following Basu (1983). Earnings-to-price is the ratio of income before extraordinary items to the market capitalization as of December $t-1$.

25. **Return on net operating assets** (rna): Following Soliman (2008). The return on net operating assets is the ratio of operating income after depreciation to lagged net operating assets.

26. **Return on assets** (roa): Following Balakrishnan, Bartov, and Faurel (2010). ROA is income before extraordinary items scaled by lagged total assets.

27. **Return on equity** (roe): Following Haugen and Baker (1996). ROE is income before extraordinary items scaled by lagged book-value of equity.

28. **Price-to-cost margin** (pcm): Following Gorodnichenko and Weber (2016) and D'Acunto, Liu, Pflueger, and Weber (2018). The price-to-cost margin is the difference between net sales and costs of goods sold divided by net sales.

29. **Profit margin** (pm): Following Soliman (2008). The profit margin is operating income after depreciation over sales.

30. **Tobin's Q** (q): Tobin's Q is total assets plus the market value of equity minus cash and short-term investments, minus deferred taxes scaled by total assets.

31. **Cash flow-to-book** ($freecf$): Following Hou, Karolyi, and Kho (2011). Cash flow to book value of equity is the ratio of operating cash flow, computed as net income plus depreciation and amortization, minus the change in working capital, and minus capital expenditures, to the firm's book value of equity.

32. **Turnover** ($turn$): Following Datar, Naik, and Radcliffe (1998). Turnover is last month's volume over shares outstanding.

33. **Capital intensity** ($d2a$): Following Gorodnichenko and Weber (2016). It is the ratio of depreciation and amortization to total assets.

34. **Operating accruals** (oa): Following Sloan (1996). Operating accruals denotes changes in non-cash working capital minus depreciation scaled by lagged total assets.

35. **SG&A to sales** ($sga2s$): It is the ratio of selling, general and administrative expenses to net sales.

Appendix A1.2 Corporate Bond

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 (2023). 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*): Following Dickerson, Robotti, and Rossetti (2023). Bond return reversal over the most recent month.

11. **Long-term reversal** (*bond_ltrev*): Following Dickerson, Robotti, and Rossetti (2023). Cumulative bond return from 48 months to 12 months before the return prediction.

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

13. **Tangibility (*tan*)**: Following Hahn and Lee (2009), defined as (0.715 × total receivables (RECT) + 0.547 × inventories (INVT) + 0.535 × 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 (2023) to examine the effect of stock on corporate bond pricing.

Appendix A1.3 Option

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.

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.

[20] See Duarte, Jones, Mo, and Khorram (2023) and Duarte, Jones, and Wang (2024), who also highlight the impact of look-ahead bias in out-of-sample option-based strategies.

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*), and Short-term reversal (*strev*)**: 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 PCA of Observable Factors

In the main context, we find that the first regressed-PCA common factor F_1^C, estimated directly from individual asset returns, is strongly correlated with $PC1$ and similarly procyclical. This finding justifies the strong common factor structure across asset classes. This appendix provides more details on the principal components of observable pricing factors referenced in Section 4.

We stack the observable factors across the three asset classes into a matrix, standardized to zero mean and unit variance:

$$\mathbf{G} = [\mathbf{G}^s \quad \mathbf{G}^b \quad \mathbf{G}^o]$$

The PCA decomposes $\mathbf{G}$ into principal components F and eigenvector weights B:

$$\mathbf{G}_{T\times L} = F_{T\times K} B_{K\times L} + \epsilon_{T\times L}.$$

We use six observable factors in each asset class, i.e., $L = 18$:

- 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]

- Six option factors: volatility level ($LEVEL$) and moneyness skewness ($SKEW$) from Büchner and Kelly (2022), option idiosyncratic volatility ($IVOL$) and illiquidity (ILQ) from Zhan, Han, Cao, and Tong (2022), and option-market factor ($MKToption$) and volatility deviation ($VOLDEV$) 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 return of the first principal component. It declines sharply during the 2008 financial crisis, the 2015–2016 global equity selloff, and the 2020 COVID crisis, consistent with the pro-cyclical pattern of the first common factor F_1^C documented in Section 4.

Table A1 reports the variance ratios explained by the principal components. 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, revealing a significant common structure among observable pricing factors across asset classes.

Table A1: Explained variance ratios of the first ten 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

[†]The explained variance ratio of each principal component is defined as $\frac{\text{Cov}(PCs,G)}{\text{Var}(G)}$ for $s = 1, ..., 10$.

To assess whether $PC1$ captures variation across all three asset classes rather than being tied to a specific class, Table A2 reports its marginal R^2 for each class, computed as the share of within-class variance explained by that component alone.

[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.

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

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
Corp 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.

$PC1$ explains 20.47% of stock, 31.72% of corporate bond, and 44.91% of option factor variation, confirming that it captures a genuinely cross-market covariation rather than variation in a single asset class. No other component achieves comparable explanatory power across all three classes simultaneously. This strong common factor structure among observable factors, from a different aspect, provides additional empirical support for the common factor structure identified in Section 4.

Appendix A3 Cross-Market Beta Loadings of Common Factors

This appendix provides more detailed analysis in Section 4 on the contribution of characteristics in factor loadings on the first common factors, and the related results for the second to tenth common factors.

Figure 3 reports the estimated B coefficients with 95% confidence intervals, computed using the weighted bootstrap procedure of Chen, Roussanov, and Wang (2021). We find that F_1^C loads significantly on managed portfolios across all three asset classes. In details, for the stock part, book assets and market capitalization dominate the beta loadings, with weights of similar magnitude but opposite signs, reflecting a value–leverage dimension in the factor structure. Notably, the book-to-market ratio itself carries negligible weight, suggesting that book assets and market capitalization jointly absorb the variation typically attributed to it. This is consistent with Kelly, Pruitt, and Su (2019), who find that the first IPCA factor's beta is similarly driven by high book assets and low market equity. For the corporate bond part, credit quality (ratings) and interest rate sensitivity (duration) are the primary dimensions driving the exposure to the common factor, with VaR also loading positively, indicating that bonds with greater downside risk have larger exposures to the first common factor (Dickerson, Mueller, and Robotti, 2023). For the option part, embedded leverage, option Greeks (gamma

and theta), and certain stock-level characteristics such as book-to-market and momentum are the dominant contributors. These characteristics broadly capture volatility risk: options whose payoffs are more sensitive to market-wide volatility movements—as reflected in higher embedded leverage and larger Greeks—load more heavily on the first common factor.

Figures A2–A4 extend this analysis to the second through tenth common factors. A consistent pattern emerges across all nine figures: each common factor loads significantly on characteristics from more than one asset class, and none concentrates its loadings exclusively within stocks, bonds, or options. Factor 2 features prominent bond illiquidity and option Greeks alongside scattered stock loadings, suggesting a liquidity-volatility dimension. Factor 3 is anchored by assets-to-market equity ($a2me$) on the stock side but retains significant bond and option loadings. Factor 6 has market beta as its largest single loading, yet bond spread and option implied volatility characteristics are also significant. Factor 7 is notable for the dominance of bond issue size, but meaningful stock and option loadings persist alongside it. Factors 8–10 are more diffuse but exhibit the same cross-asset breadth, with multiple significant bars in all three panels throughout. These results reinforce the conclusion in Section 4 that the common factors represent genuinely cross-market risk dimensions rather than reconfigured single-asset-class factors.

Appendix A4 Relation to Ludvigson and Ng (2009) factors

This appendix relates the common factors to the macro factors of Ludvigson and Ng (2009). The sample period is from July 2004 to December 2021. Tables A3 and A4 report the correlations and Shapley-Owen regression decompositions, respectively.

Ludvigson and Ng (2009) identify their factors as follows: F_1^{LN} is a "real" factor loading on employment, production, and capacity utilization; F_2^{LN} is an interest rate factor correlated with the forward-rate factor of Cochrane and Piazzesi (2005); F_3^{LN} and F_4^{LN} are inflation factors; and F_8^{LN} is a stock market factor.

Many common factors exhibit significant relation with these macro factors. The first common factor has the richest macro content, with real activity (F_1^{LN}), interest rates (F_2^{LN}), and F_7^{LN} each contributing roughly equally. The second common factor is primarily driven by the stock market factor (F_8^{LN}). The fourth common factor dominated by the interest rate factor (F_2^{LN}), with a secondary contribution from F_8^{LN}, suggesting it captures financial and monetary conditions. The sixth and seventh common factors are both strongly related

to real activity (F_1^{LN}). The eighth common factor is mainly associated with the inflation factor F_4^{LN}, although with a modest overall fit.

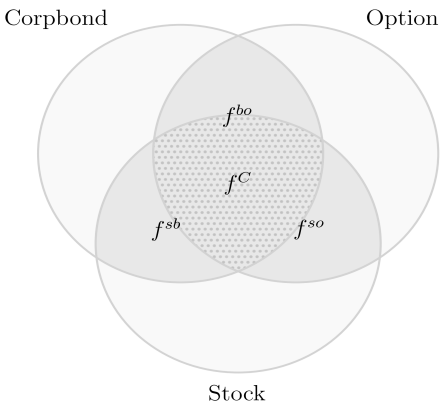
Appendix A5 More Factor Structures

First of all, we construct the common factors in each asset class based on (2.3), denoted as F^s, F^b, and F^o. Tables A5 reports the corresponding results for the single-asset-class factors. Comparing Table 11 with Tables A5, we find that common factors exhibit comparable both in-sample and out-of-sample fit compared to asset-class-specific factors for all asset markets, which is also mentioned in Section 5.1. This comparison indicates that the cross-asset commonality is largely captured by the common factors. Table A6 reports the performance of the pure-*alpha* strategy in each asset class. Comparing Table 12 with Table A6, we have several notable findings. First, the Sharpe ratios of joint pure-*alpha* strategy are usually higher than those of the pure-*alpha* strategy in the single asset class, which is due to the joint strategy aggregates the pricing errors across markets. Second, the Sharpe ratios of the pure-*alpha* strategy in stock market are always lower relative to the respective component in the joint strategy. This reflects that common factors more effectively capture the commonality in stock market compared to stock factors. Third, for some K, the Sharpe ratios of the pure-*alpha* strategy in option market are even higher compared to the respective component in the joint strategy. This is because option factors more effectively capture commonality in option market compared to common factors, and then the associated pricing errors are relatively smaller.

The main model in Section 2 focuses on factors common to all three asset classes. In this section, we extend the framework to allow for a richer factor structure that also captures commonality shared by only two asset classes. As illustrated in Figure A1, the extended structure classifies factors into three groups: *common factors* (f^C) pervasive across all three markets, *pairwise-specific factors* ($f^{P,sb}$, $f^{P,so}$, $f^{P,bo}$) shared by exactly two markets but not the third, and *asset-class-specific factors* (f^{ss}, f^{bb}, f^{oo}) that only capture variation within a single market. These three groups are mutually orthogonal by construction. Then we have that the return spaces of pairwise factors are the union of return spaces of pairwise-specific factors and common factors; the return spaces of single-asset-class factors are the union of return spaces of pairwise factors and asset-class-specific factors.

To identify pairwise factors, we first estimate a bivariate factor model for each pair of

Figure A1: Factor structure



Note: The figure shows the factor structure of managed portfolios (the whole round areas) across the three asset classes. The dotted dark area represents the common factors (f^C); the dark areas represent the pairwise factors ($f^{P,sb}$, $f^{P,so}$, $f^{P,bo}$); the light areas represent the asset-class-specific factors (f^{ss}, f^{bb}, f^{oo}).

asset classes. For stocks and corporate bonds, this takes the form:

$$\begin{aligned} R^s_t &= Z^s_{t-1} a_{sb} + Z^s_{t-1} B_{sb} f^{sb}_t + e^s_t, \\ R^b_t &= Z^b_{t-1} a_{bs} + Z^b_{t-1} B_{bs} f^{sb}_t + e^b_t, \end{aligned} \tag{A.1}$$

where f^{sb}_t are factors pervasive across both stocks and corporate bonds, estimated by applying regressed-PCA to the pooled managed portfolios of these two asset classes. Analogous bivariate models are estimated for the stock–option and bond–option pairs.

The full extended model, incorporating all three factor groups, is:

$$\begin{aligned} R^s_t &= Z^s_{t-1} a_{cs} + Z^s_{t-1}(B_{cs} f^C_t + B_{P,sb} f^{P,sb}_t + B_{so} f^{P,so}_t + B_{ss} f^{ss}_t) + \xi^s_t, \\ R^b_t &= Z^b_{t-1} a_{cb} + Z^b_{t-1}(B_{cb} f^C_t + B_{P,bs} f^{P,sb}_t + B_{P,bo} f^{P,bo}_t + B_{cc} f^{bb}_t) + \xi^b_t, \\ R^o_t &= Z^o_{t-1} a_{co} + Z^o_{t-1}(B_{co} f^C_t + B_{P,os} f^{P,so}_t + B_{P,ob} f^{P,bo}_t + B_{oo} f^{oo}_t) + \xi^o_t. \end{aligned} \tag{A.2}$$

Here each asset class loads on the common factors, the two pairwise factors relevant to it, and its own asset-class-specific factors. The key link between the bivariate model (A.1) and the full model (A.2) is that the pairwise factors f^{sb} span both the common factor space and the pairwise-specific factor space. Specifically, for a given number of factors K:

$$\begin{aligned} B_{sb} f^{sb}_t &= B_{cs} f^C_t + B_{P,sb} f^{P,sb}_t, \\ B_{bs} f^{sb}_t &= B_{cb} f^C_t + B_{P,bs} f^{P,sb}_t. \end{aligned}$$

The pairwise-specific factors $f^{P,sb}$ are thus the component of f^{sb} that is orthogonal to the common factors.

We estimate the three factor groups sequentially. First, we jointly estimate (A.1) and (A.2) to obtain common factors f^C and pairwise factors f^{sb}, f^{so}, f^{bo}. Second, we project each pairwise factor onto f^C and retain the residuals as the pairwise-specific factors $f^{P,sb}$, $f^{P,so}$, $f^{P,bo}$. Third, we apply regressed-PCA to the residuals after removing common and pairwise-specific variation to obtain the asset-class-specific factors f^{ss}, f^{bb}, f^{oo}. By construction, the three groups are mutually orthogonal: $f^C \perp f^{P,sb}, f^{P,so}, f^{P,bo} \perp f^{ss}, f^{bb}, f^{oo}$.

Table A7 compares the explanatory power of the three factor groups within each asset class, fixing the number of factors in each group. The common factors f^C explain substantially more variation in managed portfolios than either the pairwise-specific or asset-class-specific factors, across all asset classes and values of K. The explanatory power of pairwise-specific and asset-class-specific factors is broadly comparable to each other. Moreover, the total R^2_K of common factors is close across the three asset classes, which reinforces the commonality captured by the common factors. Menwhile, increases monotonically with K—a pattern not observed for the other two factor groups.

Table A8 reports analogous results for pairwise managed portfolios. Even at the pairwise level, common factors explain more variation than pairwise-specific factors, while pairwise-specific factors still contribute a substantial share. Taken together, these findings confirm that common factors capture the dominant source of cross-market commonality, while pairwise-specific and asset-class-specific factors account for additional variation, which is not spanned by the common factors.

Table A9 further report the in-sample performance of common factors and pairwise-specific factors in the explanations of individual asset returns. The findings are consist with those in Table A7-A8, where the common factors explain significantly larger variation of individual asset returns across different asset classes. For pairwise factors, the variation of common factors dominate the variation in pairwise-specific factors.

Overall, we contribute to the literature by providing several sets of factors: common factors for all three markets; pairwise and pairwise-specific factors for different market pairs; single-asset-class and asset-class-specific factors in each asset class. The different types of factors effectually capture the commonality of cross-market asset returns in different dimensions, enriching the source of factors in the literature.

Appendix A6 Robustness Checks

This appendix presents three sets of robustness checks for the main results: an alternative method for constructing out-of-sample realized factors as in (5.2); model specifications that impose $\alpha = 0$; an extended sample that includes the post-2020 period; a different approach to to estimate covariance matrix of managed portfolios in the construction of the joint MVE portfolio; and an alternative choice of regressors for the market segmentation analysis.

Appendix A6.1 Out-of-Sample Fit

Table A10 reports the out-of-sample fit using out-of-sample realized factors constructed in (5.2). Compared to Table 11, we find that the out-of-sample fit is robust to the construction of out-of-sample realized factors, although the performance of factors in (5.2) is slightly weaker. Moreover, we further find that the performance of these two sets converges with the increasing of K, where the impact of $\boldsymbol{a}$ on the out-of-sample realized factors is diminishing.

Appendix A6.2 Restricted Models

We consider restricted versions of the factor models obtained by imposing the restriction $\alpha = 0$ in equation (2.1) for each asset class,

$$R_t = Z_{t-1} B f_t + \xi_t. \tag{A.3}$$

Similarly, the multiple asset classes can be stacked into the following matrix

$$\boldsymbol{R}_t = \boldsymbol{Z}_{t-1} \boldsymbol{B} f_t^C + \boldsymbol{\xi}_t. \tag{A.4}$$

The models in (A.3) and (A.4) are the restricted counterparts of (2.3) and (2.5), respectively.

We estimate (A.3) separately for each asset class and (A.4) for the common factors across all asset classes. Table A12 and A13 report the in-sample and out-of-sample R^2's of the restricted common factor model in (A.4) and the restricted single-asset-class models in (A.3), separately. For both common and single-asset-class factor model specifications, imposing $\alpha(\cdot) = 0$ is usually associated with lower in-sample and out-of-sample R^2's relative to the unrestricted models, where the corresponding results are reported in Table 11 and A5. These findings are consistent with the rejection of $\boldsymbol{a} = 0$ documented in Section 5.2.

We next extend the out-of-sample analysis 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. Results under the

extended sample are reported in Case (1) of Table A14. Case (2) further trims options data by excluding observations below the $1st$ and above the $99th$ percentile of the return distribution in each period. In Case (1), the inclusion of the post-2020 period reduces out-of-sample fit for stocks and corporate bonds but improves it for options, as the estimation places greater weight on matching option return outliers; the performance of the pure-alpha strategy remains largely stable. In Case (2), trimming improves out-of-sample fit across all asset classes by reducing the influence of extreme option returns, but it introduces look-ahead bias that inflates out-of-sample Sharpe ratios for the options strategy.

Appendix A6.3 MVE Portfolios

Table A15 reports the annualized Sharpe ratios of MVE portfolios construed based on managed portfolios, including MVE portfolios both across and within different asset classes. Similar to Table 13, we also find the significant negative correlation between option with corporate bond component (-0.33) as well as with stock (-0.33), and the relatively weaker negative correlation between corporate bond and stock (-0.07). We compare the results in Table 13 and Table A15 based on two different ways to estimate covariance matrix, the Sharpe ratios of both joint and single-asset-class MVE portfolios constructed with managed portfolios are significantly larger than the Sharpe ratios of MVE portfolios constructed with common factors: 8.04 vs 4.22 of joint; 4.24 vs 2.98 of stock; 2.37 vs 1.58 of corporate bond; and 4.67 vs 2.64 of option. This finding reflects that the hedging relationship improves with the increasing number of factors used in the estimation of covariance matrix. It is more likely to capture stronger hedging relationship using more factors because the hedging relationship results from the opposite loadings on factors of different components.

Table A16 reports in-sample MVE portfolio performance under the restricted models. The Sharpe ratio for the joint MVE portfolio is 2.03, substantially below that of the unrestricted model in Table 13. This is as expected since the factors under unrestricted model are extracted from the covariance matrix of managed portfolios, while the factors under restricted model are extracted from the second order moment of managed portfolios. This finding further demonstrates the advantage of common factors based on unrestricted model in the approximation of MVE portfolios.

Tables A17 presents the Sharpe ratios of joint out-of-sample MVE portfolios and their associated asset-class-specific components as well as single-asset-class out-of-sample MVE portfolios for the baseline sample (July 2004–December 2019) with K varying from 1 to 20,

which is also shown in Figure (5). Table A18 extends the sample until December 2021, while Table A19 reports the corresponding results under the restricted model. By comparison of Tables A17 and Table A18, we find that the out-of-sample Sharpe ratios of joint MVE portfolios are lower with the extended sample when $K > 7$, suggesting that the highly volatile episodes worsen the out-of-sample performance of joint MVE portfolios. Meanwhile, we also find a similar pattern for the single-asset-class out-of-sample MVE portfolios based on the original and extended samples. For out-of-sample analysis, the unrestricted model also consistently delivers higher Sharpe ratios by comparing Tables A17 and Table A19, which is due to the same reason as the in-sample analysis. It also suggests that allowing for nonzero intercepts improves the performance of out-of-sample MVE portfolios. Tables A20, A21, and A22 report the bilateral correlations of asset-class-specific components in the out-of-sample MVE portfolios and their correlations with the out-of-sample realized factors in (5.2) for the baseline sample, the extended sample, and the restricted model, respectively. Overall, across all different cases, the high Sharpe ratios of out-of-sample MVE portfolios result from the bilateral hedging of asset-class-specific components, which is explained by their opposite loadings on the out-of-sample factors.

Appendix A6.4 Market Segmentation

The regression results in (7.7) based on a large set of managed portfolios might not be reliable. As a robustness check for Table 15 in the main text, Table A23 replaces the managed portfolios used as regressors in (7.7) with the ten common factors and the "arbitrage" portfolio of (5.6). Since the number of managed portfolios is large relative to the sample size, using common factors as regressors reduces dimensionality while retaining the main cross-market covariation. The conclusions in Section 7 are robust to this change, where we find significant evidence of market segmentation based on both sets of regressors. In particular, we find the large extent of segmentation with factors, which is because they capture the lower-dimensional common variation in managed portfolios.

Appendix A7 Related Figures and Tables

Table A3: Correlations between common factors and macro factors from Ludvigson and Ng (2009)†

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
F_1^{LN}	0.15**	0.07	-0.17**	0.01	0.14**	0.34***	0.32***	-0.13*	0.05	0.07
F_2^{LN}	0.30***	-0.05	0.17**	0.28***	-0.18***	-0.11	0.02	0.06	-0.10	-0.05
F_3^{LN}	-0.09	0.11	0.06	-0.01	0.10	0.10	0.14**	0.05	-0.12*	0.03
F_4^{LN}	-0.11	-0.06	0.04	-0.00	0.15**	0.18***	0.04	-0.21***	0.04	-0.03
F_5^{LN}	0.07	0.08	0.18**	0.08	-0.02	-0.07	0.01	0.17**	-0.16**	0.06
F_6^{LN}	0.17**	0.03	0.10	-0.06	0.17**	0.04	0.01	0.13*	-0.07	0.09
F_7^{LN}	0.25***	-0.21***	0.20***	0.20***	-0.30***	-0.31***	-0.13*	0.10	0.03	-0.07
F_8^{LN}	0.09	-0.25***	0.11	0.20***	-0.00	-0.07	-0.05	-0.03	-0.12*	0.09

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. F^{LN} are eight macro factors from Ludvigson and Ng (2009).

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

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
F_1^{LN}	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)	(0.00)	(0.35)	(1.67)
	[0.22]	[0.04]	[0.17]	[0.02]	[0.05]	[0.39]	[0.61]	[0.07]	[0.02]	[0.20]
F_2^{LN}	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]
F_3^{LN}	0.11	0.18	0.10	0.23*	-0.06	0.06	0.32**	0.14	-0.31***	-0.06
	(0.89)	(1.30)	(0.71)	(1.67)	(-0.62)	(0.40)	(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]
F_4^{LN}	-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]
F_5^{LN}	0.02	0.01	0.02	-0.11	0.02	-0.04	-0.10	0.07	0.09	0.12
	(0.33)	(0.10)	(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]
F_6^{LN}	0.14*	-0.03	0.17**	-0.06	0.23***	0.07	-0.03	0.05	-0.05	0.06
	(1.81)	(-0.34)	(2.30)	(-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]
F_7^{LN}	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]
F_8^{LN}	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)	(-1.60)	(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

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. F^{LN} are eight macro factors from Ludvigson and Ng (2009). The Shapley-Owen R^2's are in square brackets. Common factors and macro factors are standardized using the time-series standard deviation.

Figure A2: Estimates of coefficients B for the second to fourth common factor with 95% confidence intervals

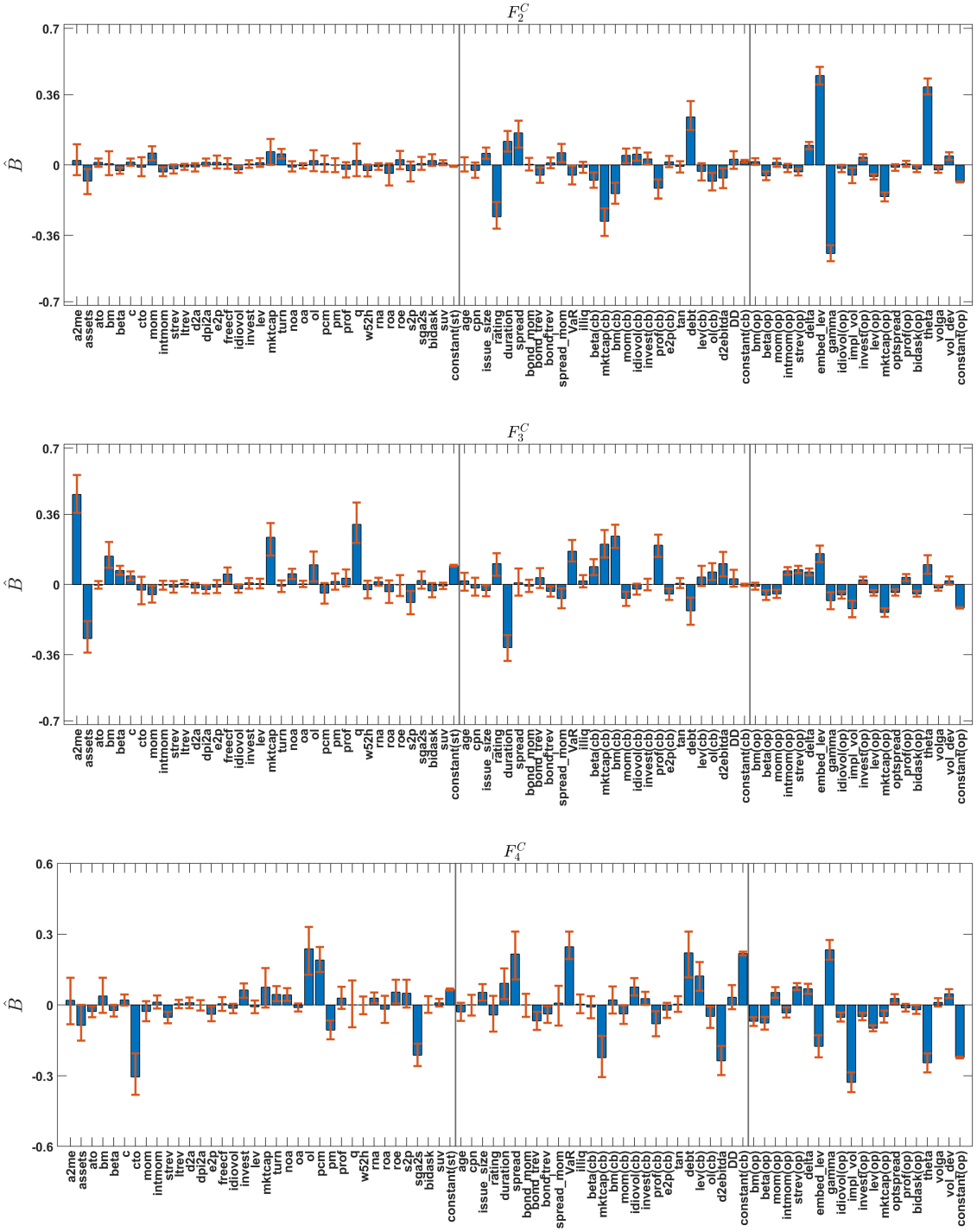


Figure A3: Estimates of coefficients B for the fifth to seventh common factor with 95% confidence intervals

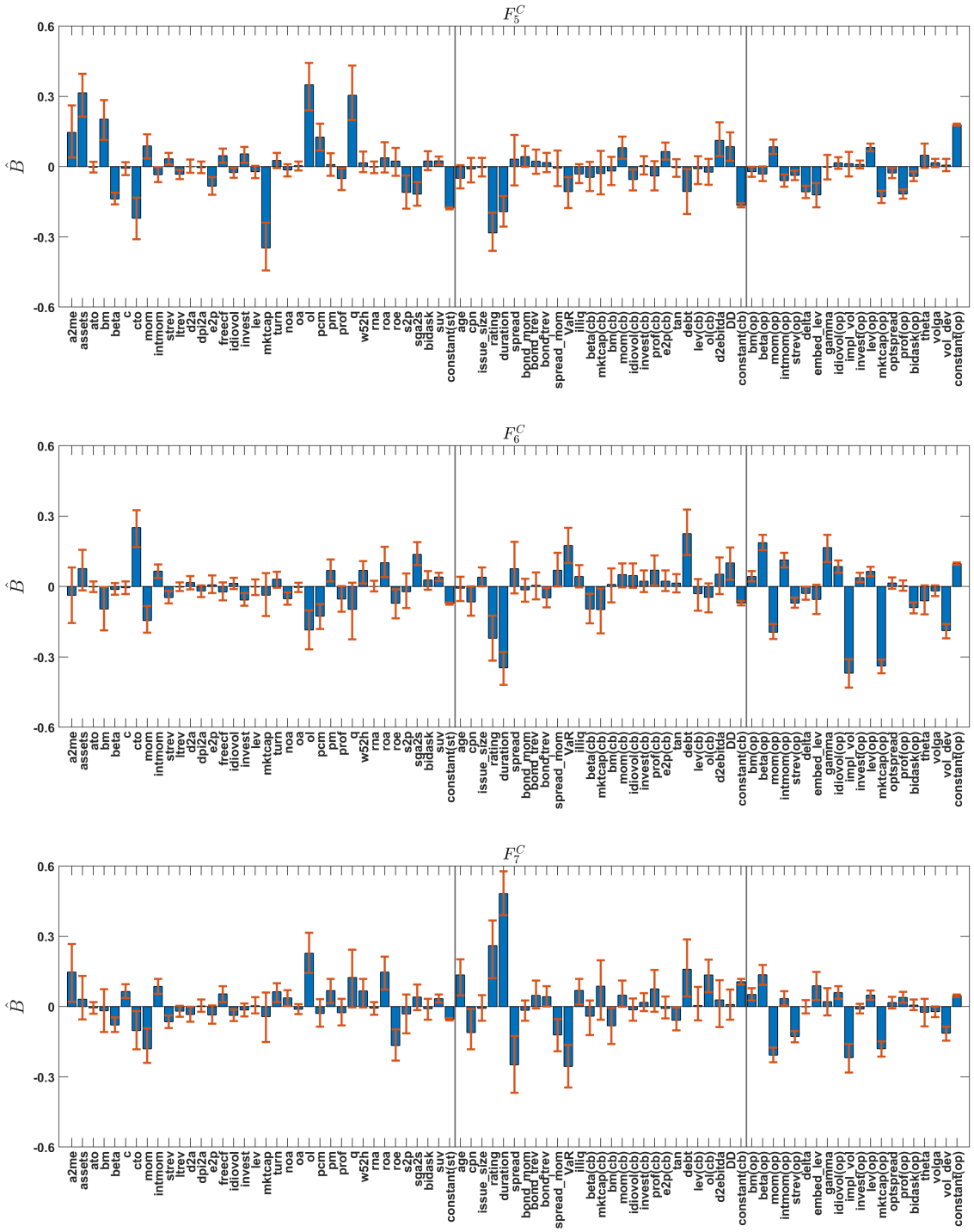


Figure A4: Estimates of coefficients B for the eighth to tenth common factor with 95% confidence intervals

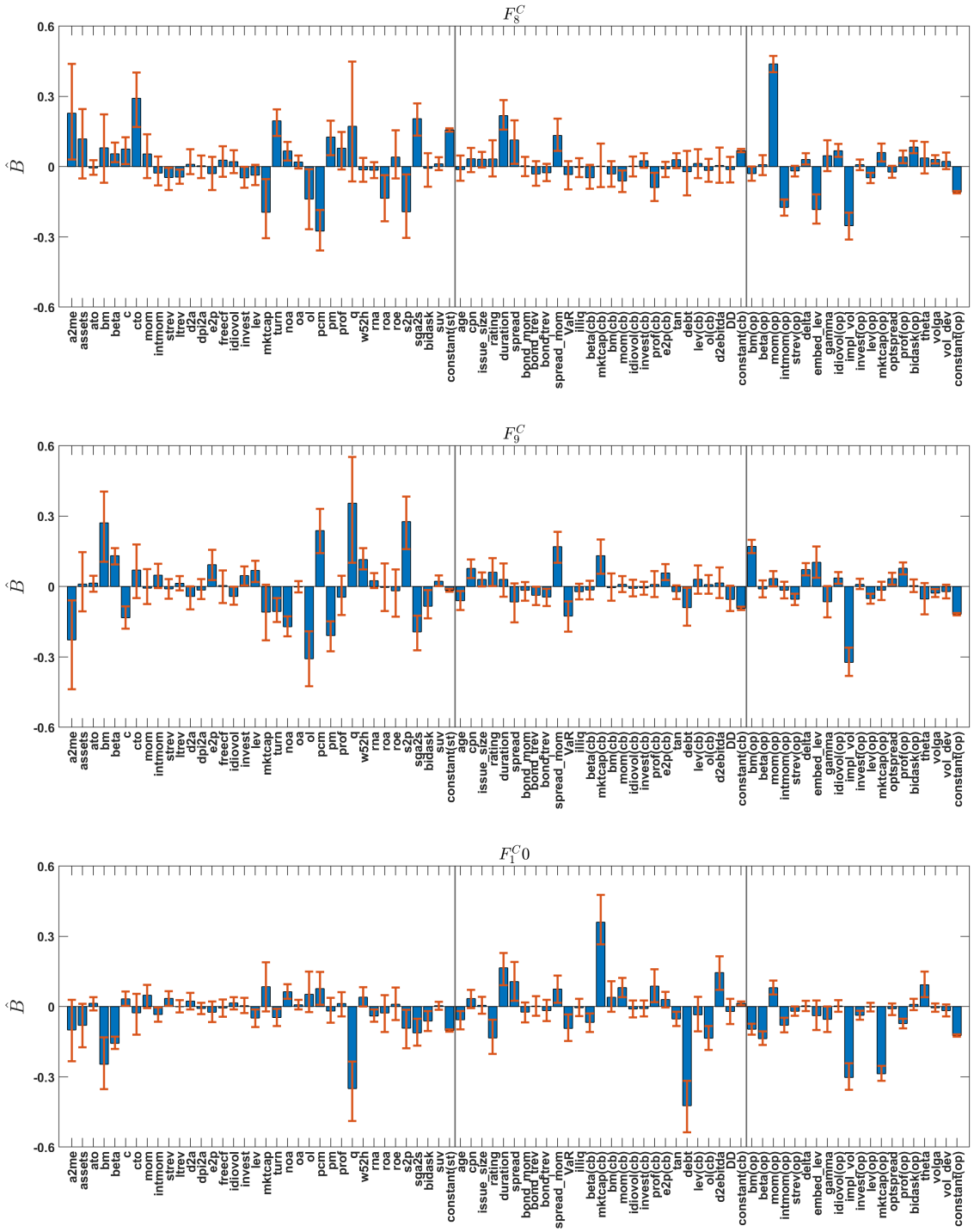


Table A5: In-sample and out-of-sample performance of the factor models for each asset class[†]

I: Stock

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	0.62	0.04	18.64	

II: Corporate bond

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	1.67	1.67	47.68	

III: Option

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	1.82	7.23	3.76
2	52.18	9.33	2.48	16.78	5.07
3	62.41	18.11	3.25	17.61	5.70
4	70.07	22.22	3.47	16.42	6.18
5	77.06	22.75	3.83	15.50	6.69
6	81.53	23.28	4.06	15.49	6.96
7	84.66	23.58	4.19	15.08	7.22
8	87.61	23.89	4.34	14.75	7.47
9	89.79	24.15	4.54	14.63	7.78
10	91.91	24.46	4.87	15.11	8.20
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.14	0.37	0.51	27.80	

[†]K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table A6: Out-of-sample performance of the pure-*alpha* strategy based on the factor models for each asset class[†]

I: Stock			
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			
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			
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

[†]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* portfolios and their associated components in (5.6).

Table A7: In-sample performance of different factors in managed portfolios[†]

Stock managed portfolios					
K	F^C	$F^{P,sb}$	$F^{P,so}$	F^{ss}	F^C+$F^{P,sb}$+$F^{P,so}$
1	21.90	2.56	3.65	14.61	32.03
2	22.69	13.94	12.72	20.19	41.18
3	33.11	17.21	17.63	17.20	55.15
4	38.29	17.21	16.52	18.09	61.55
5	48.54	10.42	12.46	18.30	67.55
6	52.26	13.09	12.08	15.89	73.82
7	54.73	15.88	16.39	14.51	77.59
8	59.49	13.88	13.38	14.14	79.99
9	65.49	10.13	11.04	11.44	83.83
10	67.94	9.24	10.83	10.26	85.79
Corporate bond managed portfolios					
K	F^C	$F^{P,sb}$	$F^{P,bo}$	F^{bb}	F^C+$F^{P,sb}$+$F^{P,bo}$
1	13.51	4.63	1.64	15.13	32.52
2	23.79	13.59	10.63	18.87	44.19
3	32.67	14.91	13.03	22.11	52.12
4	41.09	11.98	14.65	20.91	61.87
5	45.19	16.44	17.02	17.18	70.83
6	50.33	14.04	17.45	14.68	76.41
7	58.69	10.38	14.33	13.57	79.94
8	60.04	10.29	16.22	11.95	82.81
9	61.26	15.04	18.47	10.49	85.67
10	65.46	14.66	15.45	9.68	87.68
Option managed portfolios					
K	F^C	$F^{P,so}$	$F^{P,bo}$	F^{oo}	F^C+$F^{P,so}$+$F^{P,bo}$
1	9.45	8.79	17.42	18.81	37.25
2	31.07	9.63	6.23	23.81	44.66
3	34.52	12.90	16.16	19.67	58.91
4	43.20	18.49	12.19	17.53	68.21
5	45.39	18.83	18.22	17.69	71.98
6	55.51	14.90	14.38	15.52	77.66
7	58.65	12.78	14.98	15.34	79.79
8	63.76	11.21	14.71	13.02	83.96
9	66.24	11.57	13.87	12.57	85.51
10	68.93	12.41	13.59	11.04	88.04

[†] K: the number of factors specified; F^C: common factors; $F^{P,sb}$, $F^{P,so}$, and $F^{P,bo}$: pairwise specific factors; F^{ss}, F^{bb}, and F^{oo}: asset-class-specific factors. R^2, $R^2_{T,N}$, and $R^2_{N,T}$ are defined on managed portfolio pairs.

Table A8: In-sample performance of different factors in managed portfolio pairs[†]

	Stock and corporate bond managed portfolios					
	F^C			$F^{P,sb}$		
K	R^2	$R^2_{T,N}$	$R^2_{N,T}$	R^2	$R^2_{T,N}$	$R^2_{N,T}$
1	18.17	10.47	10.40	3.48	2.17	2.44
2	23.18	13.97	12.28	13.78	7.90	8.79
3	32.91	19.03	21.31	16.19	11.22	10.05
4	39.54	24.17	25.76	14.88	10.12	10.78
5	47.05	28.61	32.34	13.10	10.35	10.03
6	51.40	32.07	35.59	13.51	11.92	12.15
7	56.49	36.13	40.08	13.44	12.07	12.92
8	59.73	38.73	43.30	12.28	11.80	12.83
9	63.61	42.59	48.19	12.31	12.62	12.56
10	66.84	44.77	52.47	11.65	13.29	12.16
	Stock and option managed portfolios					
	F^C			$F^{P,so}$		
K	R^2	$R^2_{T,N}$	$R^2_{N,T}$	R^2	$R^2_{T,N}$	$R^2_{N,T}$
1	16.30	9.09	9.64	5.96	3.12	3.30
2	26.46	14.02	17.49	11.33	6.50	10.42
3	33.74	18.06	23.91	15.50	10.71	12.81
4	40.50	22.77	30.21	17.41	13.03	16.71
5	47.12	27.35	35.77	15.33	12.85	15.34
6	53.72	32.36	40.75	13.35	12.45	15.30
7	56.49	35.12	43.70	14.76	13.92	18.14
8	61.41	39.20	48.14	12.40	12.91	15.99
9	65.83	43.57	53.36	11.28	12.42	14.96
10	68.39	45.33	57.10	11.54	14.09	14.25
	Corporate bond and option managed portfolios					
	F^C			$F^{P,bo}$		
K	R^2	$R^2_{T,N}$	$R^2_{N,T}$	R^2	$R^2_{T,N}$	$R^2_{N,T}$
1	11.46	9.07	2.92	9.61	5.44	5.88
2	27.46	18.07	15.70	8.40	7.20	1.20
3	33.60	22.72	21.10	14.61	9.94	9.15
4	42.16	28.71	27.85	13.41	9.72	6.13
5	45.29	31.81	29.80	17.62	13.82	10.50
6	52.95	36.98	36.11	15.90	13.09	14.73
7	58.67	41.48	41.29	14.66	12.93	14.57
8	61.92	43.97	44.73	15.45	15.51	16.20
9	63.78	45.50	47.08	16.15	17.35	16.04
10	67.22	47.73	52.54	14.51	17.74	13.08

[†] K: the number of factors specified; F^C: common factors; $F^{P,sc}$, $F^{P,so}$, and $F^{P,bo}$: pairwise specific factors; R^2, $R^2_{T,N}$, and $R^2_{N,T}$ are defined on managed portfolio pairs.

Table A9: In-sample performance of different factors in individual returns[†]

	Stock + Corporate bond			Stock + Option			Corporate bond + Option			All	
R^2	F^C	$F^{P,sb}$	$F^C + F^{P,sb}$	F^C	$F^{P,so}$	$F^C + F^{P,so}$	F^C	$F^{P,bo}$	$F^C+F^{P,bo}$	F^C	$F^C+F^{P,sb}+F^{P,so}+F^{P,bo}$
1	6.61	0.15	6.77	5.85	1.42	6.64	6.11	6.80	10.81	6.11	13.36
2	6.70	1.81	8.52	7.46	3.34	10.63	8.87	4.84	12.19	7.67	15.15
3	7.60	1.98	9.73	9.05	2.74	11.57	11.18	3.70	15.16	9.28	17.57
4	9.01	2.91	11.80	11.17	4.79	15.08	15.47	5.85	19.45	11.83	20.34
5	11.18	2.21	13.53	12.89	4.78	16.43	17.34	5.73	21.04	13.70	21.29
6	11.59	2.30	14.13	13.78	4.50	17.33	18.73	5.49	22.50	14.61	21.99
7	12.11	2.76	14.82	14.11	4.45	17.64	19.44	5.69	23.35	15.09	22.47
8	13.05	2.55	15.57	14.87	4.03	18.12	20.09	6.19	24.77	15.87	22.85
9	13.51	2.71	16.35	15.70	4.31	19.03	21.21	5.16	25.01	16.69	23.21
10	13.92	2.55	16.68	16.13	4.20	19.48	21.63	5.02	25.45	17.11	23.54
$R^2_{T,N}$	F^C	$F^{P,sb}$	$F^C + F^{P,sb}$	F^C	$F^{P,so}$	$F^C + F^{P,so}$	F^C	$F^{P,bo}$	$F^C+F^{P,bo}$	F^C	$F^C+F^{P,sb}+F^{P,so}+F^{P,bo}$
1	2.76	0.27	3.07	2.66	0.68	3.07	2.32	2.87	5.59	2.71	7.62
2	2.76	0.98	4.27	3.80	1.87	5.77	4.48	1.58	5.77	3.85	9.11
3	4.10	0.85	5.43	5.23	0.34	5.66	5.97	2.71	8.72	5.32	11.10
4	5.04	1.10	6.91	6.20	3.03	8.64	8.07	1.01	9.72	6.58	12.95
5	6.72	2.58	8.95	7.48	3.13	9.92	9.55	0.63	10.68	8.00	13.94
6	6.94	2.66	9.36	7.55	4.01	10.56	9.35	3.51	12.76	8.06	14.64
7	7.39	2.48	9.77	7.73	3.98	10.78	9.95	3.75	13.57	8.41	15.10
8	8.08	2.34	10.31	8.42	3.32	11.15	10.76	3.76	14.63	9.10	15.55
9	8.43	2.83	10.86	8.90	3.22	11.95	11.42	3.15	14.89	9.58	15.97
10	8.97	2.96	11.23	9.50	3.19	12.39	12.11	2.66	15.54	10.18	16.33
$R^2_{N,T}$	F^C	$F^{P,sb}$	$F^C + F^{P,sb}$	F^C	$F^{P,so}$	$F^C + F^{P,so}$	F^C	$F^{P,bo}$	$F^C+F^{P,bo}$	F^C	$F^C+F^{P,sb}+F^{P,so}+F^{P,bo}$
1	-2.78	-2.24	-3.58	2.81	-1.86	1.92	2.58	2.83	6.54	2.62	9.74
2	-3.95	-1.79	-0.69	4.58	1.79	8.58	4.33	0.07	5.41	4.34	10.69
3	-3.03	-2.10	0.14	6.48	-0.96	7.97	6.23	1.68	10.83	6.22	15.73
4	-0.14	-2.92	2.11	9.73	4.46	14.80	9.56	0.39	11.99	9.51	18.70
5	2.52	-5.03	4.87	12.16	1.94	14.92	11.97	-1.33	12.63	11.93	19.47
6	2.61	-5.37	6.18	11.38	4.76	16.88	11.19	5.70	17.63	11.16	20.43
7	4.91	-3.34	7.12	11.39	4.64	16.73	11.25	5.76	18.04	11.23	21.13
8	5.95	-2.87	8.25	13.10	2.69	16.93	12.98	4.00	18.54	12.93	21.66
9	6.17	-2.92	9.10	14.41	3.00	18.47	14.29	2.54	18.49	14.23	22.07
10	6.14	-2.45	9.89	16.02	0.99	18.78	15.89	0.52	18.71	15.81	22.51

[†] K: the number of factors specified; F^C: common factors; $F^{P,sc}$, $F^{P,so}$, and $F^{P,bo}$: pairwise specific factors; R^2, $R^2_{T,N}$, and $R^2_{N,T}$ are defined on individual assets.

Table A10: Out-of-sample performance (R^2) of the common factors defined in (5.2)†

I: All asset returns			
K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	1.06	−0.04	1.40
2	1.50	3.82	2.12
3	2.09	5.92	3.08
4	1.94	5.18	2.96
5	2.02	3.31	3.08
6	2.63	5.02	3.78
7	2.81	7.27	4.31
8	2.72	7.55	4.21
9	2.77	7.23	4.31
10	2.95	7.33	4.50
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	0.22	0.08	0.30
2	0.61	4.05	1.10
3	1.09	6.16	2.04
4	0.94	5.45	1.81
5	0.87	3.55	1.60
6	1.44	5.32	2.28
7	1.87	7.66	2.97
8	1.77	7.98	2.87
9	1.79	7.60	2.95
10	1.81	7.66	2.99

†K: the number of factors specified; $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table A12: In-sample and out-of-sample performance (R^2) of the common factor model with $\alpha(\cdot) = 0$

I: All asset 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*	15.80	6.20	0.30	1.24	0.41	2.97	8.59	4.58
2	26.16	7.54	0.28	0.68	0.36	3.68	10.62	5.73
3	33.90	8.86	0.24	0.53	0.29	4.02	13.66	6.34
4	41.13	10.21	0.26	−0.21	0.35	4.24	14.67	6.64
5	47.25	12.75	0.24	−0.22	0.35	4.56	14.59	6.98
6	53.09	14.18	0.15	−0.71	0.29	4.74	14.93	7.21
7	57.62	14.41	0.13	−0.63	0.25	4.97	15.39	7.59
8	61.47	15.26	0.17	0.22	0.29	5.16	15.52	7.92
9	64.78	16.01	0.15	0.37	0.27	5.31	15.63	8.17
10	67.67	16.32	0.15	0.43	0.28	5.46	15.82	8.34

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	1.10	−0.35	8.62	11.57	7.11
2	23.15	6.11	0.38	0.83	−0.30	10.28	12.89	8.86
3	32.80	6.76	0.33	0.86	−0.38	11.12	14.44	9.71
4	36.74	6.90	0.35	0.74	−0.31	11.32	14.59	9.85
5	41.54	7.91	0.19	0.46	−0.31	11.35	14.30	9.85
6*	52.50	9.45	−0.03	−0.10	−0.14	11.66	14.73	10.17
7	53.78	9.52	−0.03	−0.09	−0.13	11.72	14.79	10.24
8	57.07	10.00	0.16	0.31	−0.07	11.94	14.95	10.44
9	63.50	10.97	0.07	0.08	−0.13	12.08	15.00	10.59
10	68.18	11.41	0.06	0.17	−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	0.08	1.96	3.91	−24.47	−5.28
2	22.71	11.20	2.53	0.03	0.72	1.89	−29.37	−10.60
3	33.05	13.36	2.36	−0.47	0.29	3.66	−24.13	−9.85
4	40.24	21.21	2.41	0.15	0.96	3.73	−25.29	−10.66
5	43.25	25.13	2.29	−0.18	1.04	6.02	−24.60	−7.29
6	46.62	28.66	2.11	−0.95	1.22	6.62	−23.93	−5.79
7*	57.96	31.43	2.09	−0.44	1.31	13.81	−15.62	1.93
8	60.52	32.06	2.18	0.88	1.39	17.06	−12.51	6.70
9	62.29	33.43	2.10	0.39	1.12	19.00	−10.90	8.87
10	64.66	33.60	2.17	0.99	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	0.23	1.26	0.67	1.56	8.99	3.11
2*	33.23	8.40	0.20	0.68	0.62	2.10	11.09	4.31
3	36.08	10.24	0.16	0.54	0.55	2.29	14.15	4.74
4	47.37	11.92	0.18	−0.23	0.60	2.52	15.21	5.09
5	58.15	15.68	0.19	−0.23	0.62	2.86	15.12	5.32
6	60.15	16.78	0.15	−0.72	0.53	2.99	15.46	5.41
7	61.98	16.86	0.12	−0.64	0.45	3.08	15.83	5.60
8	67.76	18.07	0.12	0.21	0.47	3.19	15.91	5.77
9	68.79	18.56	0.11	0.38	0.47	3.29	16.01	5.98
10	69.98	18.77	0.12	0.43	0.49	3.50	16.23	6.24

†K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table A13: In-sample and out-of-sample performance of factor models with $\alpha(\cdot) = 0$ for each asset class[†]

I: Stock

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	0.61	0.04	8.68	8.41	7.56
2	43.57	3.08	0.34	0.58	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	0.73	−0.06	12.56	15.88	11.13
5	67.96	11.32	0.11	0.19	−0.05	13.07	16.40	11.66
6	73.21	14.22	0.18	0.62	−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

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	1.19	0.43	9.47	−8.20	6.29
2	44.57	17.20	2.19	4.74	2.87	26.48	8.44	21.60
3*	59.18	30.76	1.91	4.42	2.39	30.56	14.15	25.21
4	66.96	34.97	1.76	3.90	2.17	31.54	14.85	25.99
5	73.41	37.22	2.17	4.94	2.49	33.99	19.07	28.25
6	78.26	39.33	2.20	3.18	2.26	34.58	19.25	28.90
7	81.65	40.06	2.04	2.87	2.13	35.76	20.40	30.08
8	84.57	40.82	2.10	1.40	1.78	37.69	21.15	32.44
9	87.24	42.18	2.04	1.33	1.71	38.01	20.99	32.75
10	89.32	42.90	1.98	1.90	1.49	38.36	21.35	33.19

III: Option

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	0.09	−0.70	0.38	2.09	10.27	4.44
2	53.90	8.21	−0.07	0.28	−0.04	2.51	14.26	5.34
3	64.11	16.51	−0.01	0.52	0.20	3.26	15.05	6.01
4	71.58	21.44	0.09	0.08	0.41	3.52	15.15	6.40
5	77.89	22.59	0.11	−0.06	0.45	3.83	15.40	6.82
6	82.32	23.13	0.11	0.09	0.46	4.03	15.77	7.05
7	85.45	23.38	0.12	−0.05	0.48	4.16	15.75	7.33
8	88.22	23.86	0.13	−0.05	0.50	4.30	15.60	7.62
9	90.35	24.06	0.14	0.09	0.51	4.56	15.66	7.96
10	92.20	24.52	0.13	0.28	0.51	4.84	15.57	8.27

[†]K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table A14: Out-of-sample performance (R^2) of the common factors and the pure-*alpha* strategy for the extended sample period ending December 2021†

I: All asset 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	9.99	5.35	1.87	1.91	7.99	4.48	11.96	3.26	3.66	9.82	8.69	6.77
2	4.97	4.86	1.02	2.53	11.16	5.78	7.86	2.98	2.64	12.50	12.44	8.88
3	4.67	4.23	1.10	3.07	14.62	6.54	7.41	2.62	2.82	14.56	16.48	10.20
4	3.51	3.80	0.93	3.33	14.52	6.88	6.82	2.57	2.66	15.72	16.68	10.68
5	3.41	3.76	0.91	3.55	14.39	7.18	6.75	2.53	2.67	16.25	16.62	11.11
6	4.04	3.72	1.09	3.78	14.06	7.63	6.64	2.50	2.65	17.12	16.35	11.73
7	5.01	3.74	1.34	3.83	13.02	7.82	6.96	2.45	2.84	17.43	15.41	11.96
8	4.39	3.16	1.39	4.92	14.86	8.17	5.95	2.20	2.70	17.85	17.40	12.41
9	3.85	2.89	1.33	5.04	15.48	8.46	5.46	1.93	2.82	18.36	18.19	12.85
10	3.74	3.01	1.24	6.03	15.57	8.68	4.98	1.63	3.05	18.62	18.40	13.06
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	0.11	0.25	0.49				1.31	0.25	1.49			

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	0.58	0.07				0.33	0.58	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	−2.47	0.44				1.60	−2.47	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	2.13	8.49	2.93	11.03	3.09	3.57	11.89	9.06	5.60
2	5.03	4.45	1.13	2.65	11.71	4.72	7.92	2.48	3.19	15.91	12.91	9.39
3	4.69	4.01	1.17	2.80	15.18	5.29	7.43	2.21	3.37	17.62	16.98	10.67
4	3.45	3.45	1.00	3.10	15.06	5.62	6.76	2.03	3.33	19.52	17.16	11.21
5	3.37	3.42	0.98	3.42	14.94	5.83	6.71	2.01	3.33	20.16	17.09	11.50
6	4.16	3.33	1.25	3.54	14.49	6.03	6.77	1.91	3.53	20.88	16.73	11.73
7	4.87	3.48	1.40	3.58	13.41	6.07	6.82	1.90	3.59	21.02	15.73	11.62
8	4.23	2.79	1.52	5.27	15.38	6.52	5.78	1.69	3.42	21.50	17.76	12.37
9	3.67	2.56	1.43	5.43	15.98	6.73	5.27	1.50	3.52	21.97	18.54	12.78
10	3.47	2.85	1.22	6.62	16.13	6.97	4.72	1.36	3.47	22.10	18.73	13.01
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	0.08	0.28	0.66				2.03	0.29	3.09			

†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* portfolios and their associated components in (5.6). $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table A15: In-sample Sharpe ratios of MVE portfolio and its constituents and their correlations with common factors using the covariance matrix estimated from characteristic-managed portfolios[†]

I: Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE/constituents	8.04	3.12	1.52	4.67
Single-market MVE	-	4.24	2.37	4.90
II: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.40***	0.07	0.63***
Stock	-	-	-0.07	-0.33***
CorpBond	-	-	-	-0.33***
III: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	-0.00	-0.07	0.22***	-0.06
F_2^C	0.21***	-0.10	-0.03	0.28***
F_3^C	0.10	-0.10	-0.01	0.17**
F_4^C	0.08	0.06	0.39***	-0.14**
F_5^C	-0.02	-0.05	-0.30***	0.16**
F_6^C	0.07	-0.06	-0.38***	0.28***
F_7^C	0.06	-0.24***	0.29***	0.10
F_8^C	0.09	-0.11*	0.15**	0.10
F_9^C	0.27***	0.22***	-0.15**	0.16**
F_{10}^C	0.20***	0.05	0.01	0.15**

[†] The joint MVE portfolio is constructed with the managed portfolios. Panel (I) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class-specific MVE portfolios. Panel (II) reports correlations among the constituents in 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.

Table A16: In-sample Sharpe ratios of MVE portfolio and its constituents and their correlations with common factors when $\alpha(\cdot) = 0^{\dagger}$

I: Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE/constituents	2.03	2.10	1.00	0.37
Single-market MVE	-	2.78	1.36	2.61

II: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.24***	0.19***	0.73***
Stock	-	-	-0.06	-0.22***
CorpBond	-	-	-	-0.35***

III: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	-0.10	-0.30***	0.34***	-0.14**
F_2^C	-0.07	0.00	-0.05	-0.04
F_3^C	-0.11	0.14**	0.06	-0.21***
F_4^C	-0.03	0.11*	0.34***	-0.28***
F_5^C	-0.09	-0.01	-0.29***	0.07
F_6^C	-0.04	0.08	0.20***	-0.19***
F_7^C	0.00	0.00	-0.07	0.04
F_8^C	-0.09	0.09	0.07	-0.17**
F_9^C	0.00	0.13*	-0.14**	0.02
F_{10}^C	-0.01	-0.04	0.01	0.00

† The joint MVE portfolio is constructed with $K = 10$, where its constituents is defined in (6.5). Panel (I) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class-specific MVE portfolios. Panel (II) reports correlations among the constituents in the joint MVE portfolio. Panel (III) reports correlations between the constituents of the joint MVE portfolio and the common factors.

Table A17: Out-of-sample Sharpe ratios of joint and single-asset-class 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]

[†] 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 A18: Out-of-sample Sharpe ratios of joint and single-asset-class 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]

† 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 A19: Out-of-sample Sharpe ratios of joint and single-asset-class MVE portfolios with $\alpha(\cdot) = 0^{\dagger}$

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]

† 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 A20: Anatomy of out-of-sample MVE portfolio[†]

I: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.28***	-0.00	0.91***
Stock	-	-	-0.18**	-0.12
CorpBond	-	-	-	-0.09

II: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	-0.05	-0.23***	0.25***	0.01
F_2^C	0.12	-0.19**	0.19**	0.18**
F_3^C	0.06	0.04	0.08	0.03
F_4^C	0.36***	0.13	-0.09	0.33***
F_5^C	0.15*	0.17*	-0.13	0.10
F_6^C	-0.21**	0.15*	-0.07	-0.27***
F_7^C	-0.27***	-0.16*	-0.05	-0.20**
F_8^C	-0.13	0.06	0.18**	-0.19**
F_9^C	-0.22**	0.17*	-0.17*	-0.27***
F_{10}^C	-0.20**	0.07	-0.18**	-0.20**
F_{11}^C	-0.17*	0.09	0.03	-0.22**
F_{12}^C	-0.07	0.20**	-0.17*	-0.14
F_{13}^C	0.15*	0.08	-0.18**	0.15*
F_{14}^C	-0.28***	-0.02	-0.09	-0.26***
F_{15}^C	0.03	-0.10	0.03	0.07
F_{16}^C	-0.00	-0.07	-0.02	0.03
F_{17}^C	-0.06	-0.02	0.01	-0.06
F_{18}^C	0.24***	0.04	-0.01	0.23**
F_{19}^C	-0.01	0.02	0.18**	-0.05
F_{20}^C	0.01	-0.15*	0.02	0.07

[†] Panel I reports correlations among the constituents in the joint MVE portfolio. Panel II reports correlations between the constituents of the joint MVE portfolio and common factors.

Table A21: Anatomy of out-of-sample MVE portfolio for the extended sample period ending December 2021†

I: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.30***	0.05	0.93***
Stock	-	-	-0.10	-0.05
CorpBond	-	-	-	-0.05

II: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	0.15*	-0.07	0.21**	0.15*
F_2^C	-0.07	-0.10	0.14*	-0.05
F_3^C	0.33***	-0.02	0.06	0.34***
F_4^C	0.04	-0.02	-0.13	0.07
F_5^C	-0.04	-0.01	-0.14*	-0.02
F_6^C	0.24***	0.09	0.03	0.21***
F_7^C	0.18**	-0.06	0.01	0.21**
F_8^C	-0.53***	-0.02	0.06	-0.55***
F_9^C	-0.36***	0.08	-0.11	-0.39***
F_{10}^C	-0.48***	-0.01	-0.09	-0.49***
F_{11}^C	0.37***	0.03	0.04	0.37***
F_{12}^C	-0.51***	0.03	-0.11	-0.53***
F_{13}^C	-0.39***	0.01	-0.13	-0.40***
F_{14}^C	-0.27***	-0.02	-0.08	-0.26***
F_{15}^C	0.52***	0.00	0.02	0.54***
F_{16}^C	0.55***	0.03	0.06	0.56***
F_{17}^C	0.33***	0.01	0.03	0.34***
F_{18}^C	0.58***	0.06	0.03	0.58***
F_{19}^C	0.48***	0.05	0.15*	0.46***
F_{20}^C	-0.44***	-0.07	-0.01	-0.43***

† Panel I reports correlations among the constituents in the joint MVE portfolio. Panel II reports correlations between the constituents of the joint MVE portfolio and common factors.

Table A22: Anatomy of out-of-sample MVE portfolio with restriction $\alpha(\cdot) = 0^{\dagger}$

I: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.41***	-0.01	0.88***
Stock	-	-	-0.02	-0.03
CorpBond	-	-	-	-0.19**
II: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	0.02	-0.15*	0.36***	0.02
F_2^C	-0.04	-0.04	0.06	-0.03
F_3^C	-0.04	0.10	0.04	-0.10
F_4^C	0.29***	0.22**	-0.18**	0.24***
F_5^C	0.04	0.15*	-0.19**	0.01
F_6^C	-0.42***	-0.06	-0.06	-0.41***
F_7^C	-0.04	-0.08	0.16*	-0.03
F_8^C	0.12	0.30***	0.07	-0.03
F_9^C	-0.09	0.17*	-0.26***	-0.13
F_{10}^C	-0.10	0.02	-0.16*	-0.09
F_{11}^C	-0.15*	0.02	-0.12	-0.15
F_{12}^C	-0.02	0.08	-0.15*	-0.04
F_{13}^C	0.28***	-0.00	-0.18**	0.34***
F_{14}^C	-0.07	-0.07	0.12	-0.07
F_{15}^C	0.24***	-0.08	0.09	0.28***
F_{16}^C	0.06	-0.02	-0.08	0.09
F_{17}^C	0.14	0.06	0.08	0.11
F_{18}^C	0.24***	0.04	-0.02	0.25***
F_{19}^C	-0.07	-0.04	0.15*	-0.09
F_{20}^C	-0.00	-0.17*	-0.05	0.09

† Panel I reports correlations among the constituents in the joint MVE portfolio. Panel II reports correlations between the constituents of the joint MVE portfolio and common factors.

Table A23: Market distances based on regression approach with common and pairwise factors†

K	δ^C_{s-b}	δ^C_{s-o}	δ^C_{b-o}	δ^{sb}_s	δ^{sb}_b	δ^{sb}_{s-b}	δ^{so}_s	δ^{so}_o	δ^{so}_{s-o}	δ^{bo}_b	δ^{bo}_o	δ^o_{b-o}
1	2.00*	-1.66	-3.66**	0.34	1.65*	-1.32	2.00***	1.32	0.68	-4.82***	1.28	-6.09***
	(1.84)	(-0.95)	(-2.11)	(0.47)	(1.87)	(-1.15)	(2.61)	(0.84)	(0.45)	(-5.55)	(1.48)	(-5.07)
2	-1.96	2.26	4.22***	0.84	-0.75	1.59	3.25**	-1.36	4.61***	3.55***	1.43	2.12
	(-1.28)	(1.61)	(2.95)	(0.76)	(-1.23)	(1.37)	(2.59)	(-1.38)	(3.46)	(5.40)	(1.08)	(1.41)
	[0.07]	[0.07]	[0.00]	[0.70]	[0.15]	[0.14]	[0.04]	[0.13]	[0.00]	[0.00]	[0.29]	[0.00]
3	-1.16	-5.21***	-4.06***	0.43	1.10	-0.66	0.61	-0.96	1.57	-0.80	0.19	-0.99
	(-1.06)	(-3.47)	(-2.92)	(0.80)	(1.42)	(-0.66)	(1.43)	(-0.79)	(1.33)	(-1.33)	(0.22)	(-0.88)
	[0.09]	[0.00]	[0.00]	[0.84]	[0.10]	[0.24]	[0.00]	[0.25]	[0.00]	[0.00]	[0.40]	[0.00]
4	0.66	-0.55	-1.21	-0.13	-1.33**	1.19	-4.26***	0.52	-4.78***	1.57***	-1.47	3.04***
	(0.60)	(-0.52)	(-1.06)	(-0.23)	(-2.17)	(1.57)	(-4.95)	(1.12)	(-5.14)	(6.41)	(-1.64)	(3.70)
	[0.17]	[0.00]	[0.00]	[0.75]	[0.03]	[0.19]	[0.00]	[0.35]	[0.00]	[0.00]	[0.32]	[0.00]
5	-0.54	0.43	0.97	0.79	-0.66**	1.46	0.35	0.64	-0.29	-2.61***	-0.51	-2.10**
	(-0.64)	(0.39)	(0.90)	(0.74)	(-2.03)	(1.29)	(0.82)	(0.75)	(-0.38)	(-6.08)	(-0.71)	(-2.53)
	[0.23]	[0.00]	[0.00]	[0.79]	[0.04]	[0.10]	[0.00]	[0.35]	[0.00]	[0.00]	[0.23]	[0.00]
6	0.66	-3.02***	-3.68***	0.13	0.45	-0.33	0.65	0.87	-0.22	4.10***	0.98	3.12***
	(0.59)	(-2.68)	(-4.43)	(0.24)	(0.71)	(-0.48)	(1.16)	(1.22)	(-0.24)	(7.88)	(1.37)	(3.94)
	[0.26]	[0.00]	[0.00]	[0.55]	[0.05]	[0.15]	[0.00]	[0.46]	[0.00]	[0.00]	[0.28]	[0.00]
7	1.06	2.35*	1.29	0.22	-1.40**	1.62**	2.04***	1.14	0.90	-2.41***	1.27*	-3.68***
	(1.41)	(1.84)	(1.15)	(0.45)	(-2.60)	(2.48)	(6.72)	(1.25)	(1.01)	(-6.48)	(1.84)	(-4.57)
	[0.27]	[0.00]	[0.00]	[0.61]	[0.03]	[0.02]	[0.00]	[0.58]	[0.00]	[0.00]	[0.38]	[0.00]
8	1.57*	-1.06	-2.62***	0.21	-0.99*	1.19*	2.78***	0.15	2.63***	-2.19***	0.52	-2.71***
	(1.96)	(-1.17)	(-2.75)	(0.46)	(-1.94)	(1.77)	(4.94)	(0.24)	(3.09)	(-5.24)	(1.13)	(-3.70)
	[0.09]	[0.00]	[0.00]	[0.64]	[0.05]	[0.02]	[0.00]	[0.28]	[0.00]	[0.00]	[0.07]	[0.00]
9	1.65**	-0.77	-2.41**	0.76	-0.49*	1.25**	1.23***	-1.71***	2.94***	-0.35	-0.14	-0.21
	(2.26)	(-0.84)	(-2.51)	(1.25)	(-1.84)	(2.03)	(2.69)	(-2.62)	(3.60)	(-1.33)	(-0.22)	(-0.27)
	[0.04]	[0.00]	[0.00]	[0.61]	[0.00]	[0.01]	[0.00]	[0.12]	[0.00]	[0.00]	[0.10]	[0.00]
10	-0.40	-1.53	-1.13	0.57	0.30	0.26	-1.16**	-0.07	-1.09*	-1.76***	-0.19	-1.57***
	(-0.59)	(-1.55)	(-1.24)	(0.89)	(0.94)	(0.42)	(-2.37)	(-0.17)	(-1.75)	(-4.50)	(-0.58)	(-2.99)
	[0.05]	[0.00]	[0.00]	[0.68]	[0.00]	[0.01]	[0.00]	[0.12]	[0.00]	[0.00]	[0.12]	[0.00]

† K denotes the number of factors. Based on the regressions in (7.7) for $X \in \{A, B\}$ and $A, B \in \{s, b, o\}$, δ^C_X and δ^{AB}_X are reported with t-statistics in parentheses and p-values for GRS-statistics in square brackets; $\delta^C_{A-B} = \delta^C_A - \delta^C_B$ and $\delta^{AB}_{A-B} = \delta^{AB}_A - \delta^{AB}_B$ are reported with t-statistics in parentheses and p-values for statistics of (7.8) in square brackets.

Appendix B1 Nonlinear Models

This appendix presents results from the nonlinear model extension, in which $\alpha(\cdot)$ and $\beta(\cdot)$ are approximated by B-splines with one internal knot following Chen, Roussanov, and Wang (2021). To mitigate multicollinearity among characteristics in the regressed-PCA step, we employ a subset of characteristics selected by the magnitude of Fama-MacBeth t-statistics from the initial 60-period training sample: 18 for stocks (*asset*, *ato*, *beta*, *c*, *strev*, *d2a*, *idiovol*, *lev*, *mktcap*, *turn*, *pcm*, *pm*, *prof*, *w52h*, *rna*, *roa*, *sga2s*, *suv*), 14 for corporate bonds (*age*, *cpn*, *duration*, *bond_strev*, *spread_mom*, *VaR*, *illiq*, *beta*, *mktcap*, *mom*, *idiovol*, *prof*, *tan*, *DD*), and 10 for options (*beta*, *gamma*, *idiovol*, *impl_vol*, *invest*, *lev*, *mktcap*, *optspread*, *theta*, *volga*). The number of resulting managed portfolios in the nonlinear model is matched to that of the linear model. Throughout, we compare nonlinear results against their linear counterparts in the main text and find the main conclusions are broadly robust.

Appendix B1.1 Commonality

Table B1 reports correlations between the nonlinear common factors and the eighteen observable factors. Consistent with Table 2, the leading common factors display significant correlations spanning all three asset classes simultaneously. The first common factor remains highly correlated with market, credit risk, and option-market factors, confirming that the nonlinear specification continues to identify genuinely cross-market factors.

Table B2 regresses the nonlinear common factors on observable factors. The adjusted R^2's range from 21% to 76%, generally higher than the 19% to 57% reported in the linear case (Table 3), indicating that observable factors span the nonlinear common factors more closely. Nonetheless, the intercepts remain positive and significant for most factors, confirming that the common factors continue to carry additional risk premia beyond existing observable factors, consistent with the linear findings.

Tables B3 and B4 examine the cross-market anatomy of the nonlinear common factors. The first common factor remains strongly correlated with the leading factors from all three asset classes: 0.80 with the first stock factor, 0.91 with the first corporate bond factor, and 0.53 with the first option factor. In the variance decomposition of Table B4, the bond component accounts for 51% of the variation in the first common factor—substantially higher than the 29% in the linear case (Table 5)—while the stock component contributes 38% (versus 57%) and options 12% (versus 14%). This shift suggests that using a subset of characteristics

leads the nonlinear specification to draw relatively more on corporate bond information in constructing the first common factor, while all three asset classes continue to contribute meaningfully.

Appendix B1.2 Relation to Macro-Financial Variables

Table B5 reports correlations between the nonlinear common factors and the macro-financial variables. The pattern closely parallels Table 6: the first common factor is negatively correlated with financial uncertainty and the VIX, and positively correlated with the intermediary capital factor HKM, confirming its pro-cyclical nature. The second and third factors retain their respective sensitivities to monetary conditions and real economic activity.

Table B6 summarizes the regression of nonlinear common factors on macro-financial variables via Shapley–Owen R^2 decomposition. The adjusted R^2 for the first factor reaches 49.5%, higher than the 38.6% in the linear case (Table 7), indicating stronger macro-financial content in the nonlinear factors. HKM remains the dominant explanatory variable for the first factor. The pattern for higher-order factors—with monetary policy variables leading for the second factor and real activity variables for the third—is also preserved.

Table B7 decomposes the first common factor's macro relations by asset-class constituent, corresponding to Table 8 in the main text. The option component exhibits the strongest macro link (adjusted R^2 of 48%), closely followed by corporate bonds (45%), with stocks slightly lower (26%). This contrasts with the linear case, where stock and bond components were the primary drivers. The difference likely reflects the effect of nonlinear specification, which strengthens the option component's contribution to macro-relevant variation.

Table B8 reports forecasting and nowcasting results using the nonlinear common factors. The results closely parallel Table 9: the factors significantly forecast core inflation, consumption growth, and industrial production growth (Panel I), and effectively nowcast financial conditions including HKM, $\Delta(VIX)$, and financial uncertainty (Panel II). These results confirm that the systematic macroeconomic and financial market information embedded in the common factors is robust to the nonlinear specification.

Appendix B1.3 Factor Pricing and Portfolio Performance

Table B9 reports Sharpe ratios of the nonlinear common and asset-class-specific factors. As in Table 10, common factors carry significant Sharpe ratios. The first common factor

achieves an in-sample Sharpe ratio of 0.86 and an out-of-sample Sharpe ratio of 0.81, with the options constituent delivering high risk-return tradeoffs.

Table B10 reports the in-sample and out-of-sample R^2's of the nonlinear common factor model, corresponding to Table 11 in the main text. The nonlinear model delivers broadly comparable in-sample explanatory power for managed portfolios and individual asset returns across all three markets. Out-of-sample fit is also of similar magnitude, confirming that the nonlinear specification does not significantly degrade predictive performance relative to the linear benchmark.

Table B11 reports the out-of-sample performance of the pure-alpha strategy under the nonlinear model, corresponding to Table 12. The joint pure-alpha portfolio continues to deliver high Sharpe ratios, at levels comparable to or somewhat above those of the linear model, and the results remain high as the number of factors increases. The options component again accounts for the largest share of pure-alpha returns. These findings confirm that significant mispricing persists under the nonlinear specification.

Table B12 reports in-sample MVE portfolio performance. The joint MVE portfolio achieves an in-sample Sharpe ratio of 4.30, modestly above the 4.22 of the linear model in Table 13. Importantly, the cross-asset hedging properties are stronger under the nonlinear model: the correlation between the stock and option constituents is -0.38 and significant (versus -0.03 in the linear model), and between corporate bonds and options is -0.40 (versus -0.32). The more pronounced negative correlations reflect larger offsetting exposures to common factors, which drive greater volatility reduction in the joint portfolio and account for its modestly higher Sharpe ratio.

Figure B5 (Table B18) extends the comparison to out-of-sample MVE portfolios. The peak out-of-sample joint Sharpe ratio reaches 3.62 at $K = 20$, compared with 2.94 at $K = 14$ under the linear model (Table A17). The nonlinear specification in the model achieves better out-of-sample portfolio performance, and the joint portfolio outperforms all single-asset-class benchmarks by a wider margin than in the linear case.

Appendix B1.4 Market Segmentation

Tables B13, B14, and B15 report market segmentation results under the nonlinear specification, corresponding to their linear counterparts in the main text. The evidence for significant market segmentation is robust to the nonlinear specification. At $K = 10$, the distance between stock and option markets is 94.6 ($p = 0.01$) and between corporate bond and option

markets is 116.0 ($p < 0.01$), consistent with the linear findings, confirming that the degree of segmentation between options and the other two markets is substantial and is not an artifact of the linear functional form.

Appendix B1.5 Related Figures and Tables

Figure B1: Cumulative returns of the first five common factors (F^C)

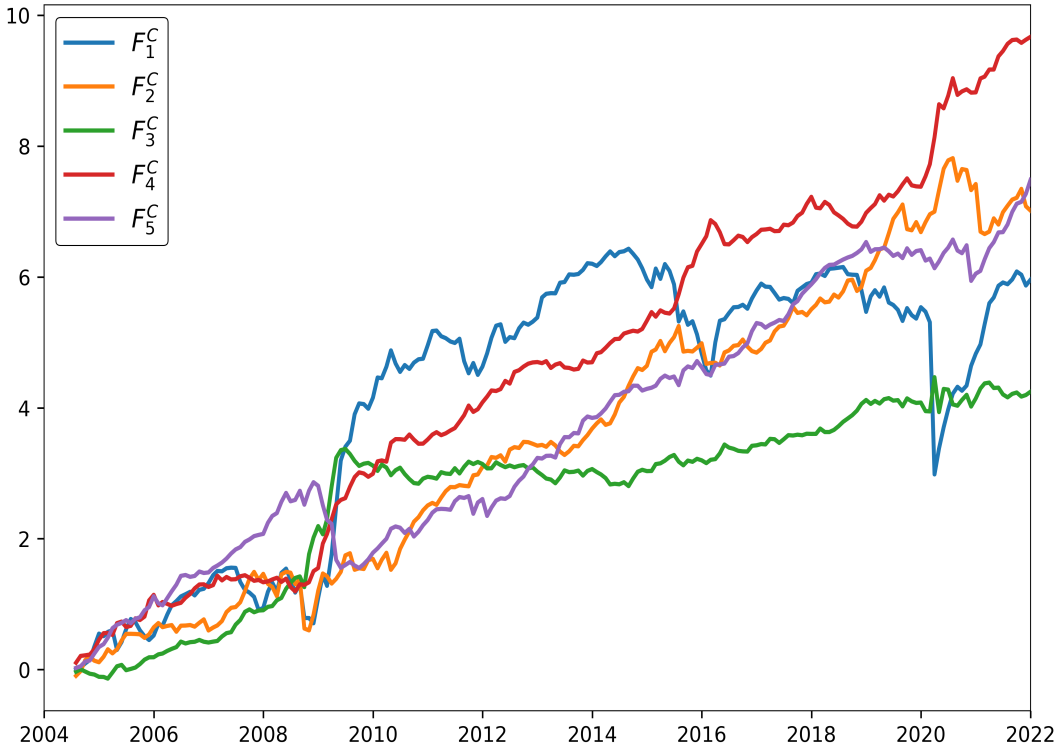


Table B1: Correlations between common factors and observable factors[†]

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
$MKTstock$	0.54***	0.16**	-0.26***	-0.18***	-0.11	0.02	-0.27***	0.26***	-0.02	0.01
SMB	0.40***	-0.09	-0.03	-0.11	-0.06	0.07	-0.13*	0.22***	0.14**	-0.07
HML	0.39***	-0.49***	-0.11	-0.11	0.28***	0.26***	-0.03	0.14**	-0.08	0.16**
RMW	-0.14**	-0.08	-0.01	0.04	0.18***	0.15**	0.14**	-0.28***	-0.03	0.24***
CMA	0.04	-0.48***	-0.01	0.14**	0.15**	0.18**	-0.01	0.02	-0.08	0.10
MOM	-0.62***	0.18***	-0.11	-0.10	0.23***	-0.06	-0.01	-0.13*	0.05	-0.23***
$MKTbond$	0.52***	0.43***	-0.30***	0.14**	-0.18**	0.13*	-0.37***	-0.17**	-0.11	0.05
CRF	0.64***	-0.03	-0.20***	-0.20***	-0.16**	-0.16**	-0.02	0.31***	-0.01	0.18***
LRF	0.52***	0.26***	-0.02	0.25***	-0.12*	-0.15**	-0.12*	-0.13*	-0.08	0.00
LTR	0.51***	0.05	0.30***	-0.03	-0.09	0.16**	-0.12*	0.02	-0.10	-0.01
$MOMB$	-0.65***	-0.16**	-0.28***	0.03	0.04	-0.03	-0.06	0.11	0.05	-0.09
$REV*$	0.31***	0.18***	-0.03	0.08	0.01	0.05	-0.01	-0.18***	-0.05	-0.10
$MKToption$	0.41***	0.33***	-0.15**	-0.22***	0.08	0.27***	-0.07	0.17**	0.28***	0.12*
$LEVEL$	0.49***	0.43***	-0.18***	-0.15**	0.12*	0.28***	-0.13*	0.17**	0.26***	0.24***
$SKEW$	0.39***	0.35***	-0.10	-0.14**	0.08	0.26***	-0.08	0.18***	0.01	0.25***
$IVOL$	0.22***	0.22***	-0.05	-0.19***	-0.06	0.12*	0.07	0.14*	0.25***	-0.02
ILQ	0.21***	0.01	-0.14**	-0.23***	-0.14**	0.09	-0.06	0.14**	0.23***	-0.07
$VOLDEV$	0.12*	0.29***	-0.06	-0.15**	-0.11	0.24***	0.21***	0.18***	0.14**	-0.04

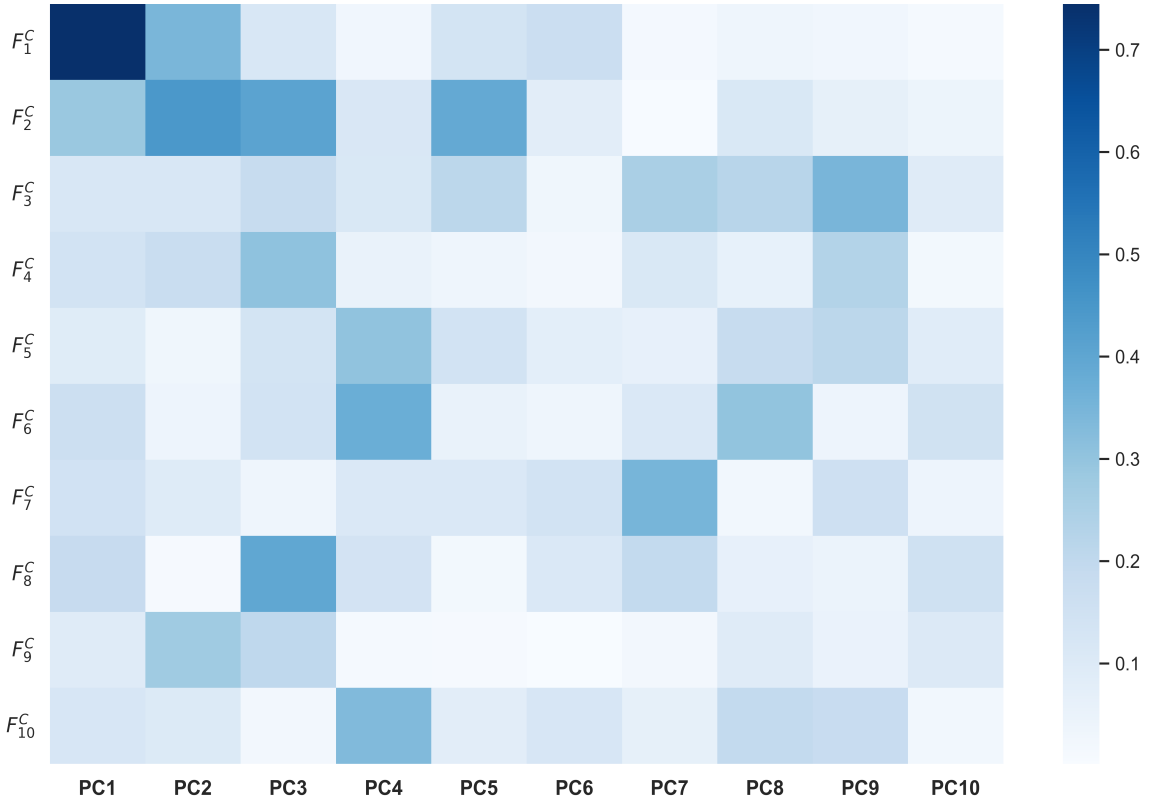
[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. The observable factors include six stock factors ($MKTstock$, SMB, HML, RMW, CMA, MOM), six corporate bond factors ($MKTbond$, CRF, LRF, $BONDMOM$, $REV*$, LTR), and six option factors ($MKToption$, $LEVEL$, $SKEW$, $IVOL$, ILQ, $VOLDEV$). See Appendix A2 for details on these observable factors.

Table B2: Regression of common factors on observable factors†

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
(Intercept)	0.02***	0.03***	0.04***	0.05***	0.04***	0.01	0.01***	0.01	0.03***	0.01***
	(2.87)	(3.86)	(5.87)	(5.30)	(7.16)	(1.18)	(2.77)	(1.46)	(5.98)	(2.99)
$MKTstock$	0.00	0.00	-0.00	-0.01	0.00	-0.00	-0.01***	0.00***	-0.00**	-0.00**
	(0.70)	(0.80)	(-0.73)	(-1.25)	(0.16)	(-0.57)	(-2.93)	(3.37)	(-2.05)	(-2.11)
SMB	0.01***	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	0.01***	-0.00
	(2.72)	(0.08)	(1.52)	(0.59)	(-0.43)	(1.02)	(-0.68)	(0.47)	(3.27)	(-0.78)
HML	0.01***	-0.01***	-0.01***	-0.01	0.02***	0.01***	-0.00	-0.00	-0.01***	-0.00
	(2.97)	(-5.32)	(-2.73)	(-1.20)	(5.50)	(3.51)	(-0.91)	(-1.36)	(-3.03)	(-0.92)
RMW	0.00	-0.01	0.00	-0.00	0.00	0.01**	0.00	-0.01**	-0.00	0.01***
	(0.24)	(-1.47)	(0.80)	(-0.82)	(1.18)	(2.01)	(1.05)	(-2.40)	(-0.16)	(2.91)
CMA	0.00	-0.02***	-0.01	0.01**	-0.01	0.01**	0.00	0.00	0.00	0.00
	(0.73)	(-4.24)	(-1.36)	(2.35)	(-1.18)	(2.13)	(0.54)	(1.21)	(0.56)	(1.48)
MOM	-0.01***	0.01**	-0.01***	-0.01**	0.01***	-0.00	-0.00	-0.00**	-0.00**	-0.00
	(-3.21)	(2.44)	(-3.00)	(-2.22)	(2.91)	(-0.78)	(-0.85)	(-2.24)	(-2.49)	(-1.62)
$MKTbond$	-0.46	1.84***	-4.10***	1.08*	-1.53***	1.95***	-2.41***	-2.02***	-1.35***	-0.47
	(-0.41)	(3.61)	(-7.69)	(1.90)	(-2.76)	(2.58)	(-5.65)	(-3.95)	(-3.47)	(-1.27)
CRF	1.53**	-0.80***	-1.82***	-0.39	-0.91**	-1.87***	0.87**	0.62	-0.35	0.61***
	(2.00)	(-3.21)	(-3.07)	(-0.50)	(-2.46)	(-6.41)	(2.03)	(1.59)	(-1.49)	(2.67)
LRF	5.51***	0.56	-0.05	2.50***	0.59	-4.41***	1.37*	0.10	0.57	-0.09
	(3.69)	(0.78)	(-0.06)	(3.10)	(0.56)	(-3.51)	(1.82)	(0.12)	(0.81)	(-0.14)
LTR	-0.35	-0.81	4.26***	-1.06	-0.67	2.81***	-1.12	-0.10	-1.12**	-0.63
	(-0.24)	(-1.41)	(3.04)	(-1.10)	(-1.07)	(3.68)	(-1.02)	(-0.16)	(-2.16)	(-1.16)
$MOMB$	-3.04***	-0.30	-2.08***	0.78	-0.89**	0.00	-0.78	0.85***	0.17	0.10
	(-4.82)	(-0.82)	(-2.88)	(1.44)	(-2.37)	(0.01)	(-1.34)	(2.60)	(0.48)	(0.26)
$REV*$	1.91**	0.62**	-0.25	0.60	0.53	0.09	0.15	-0.81	-0.23	-0.57**
	(2.36)	(1.98)	(-0.40)	(0.79)	(1.54)	(0.24)	(0.28)	(-1.53)	(-0.86)	(-2.23)
$MKToption$	-0.00	-0.01	-0.00	0.01	0.00	0.02	0.01	-0.01	0.02*	-0.00
	(-0.17)	(-0.36)	(-0.05)	(0.33)	(0.23)	(1.35)	(0.90)	(-1.22)	(1.85)	(-0.18)
$LEVEL$	0.03***	0.02***	-0.00	0.01	0.02***	0.00	-0.01	0.01	0.03***	0.01**
	(2.90)	(2.60)	(-0.64)	(0.66)	(3.09)	(0.33)	(-1.33)	(1.15)	(3.95)	(2.17)
$SKEW$	-0.05***	0.02	0.04**	-0.03	-0.02	0.01	0.03**	0.01	-0.05***	0.01
	(-2.69)	(1.19)	(2.46)	(-1.44)	(-0.92)	(0.42)	(2.05)	(1.22)	(-3.40)	(1.22)
$IVOL$	-0.00	0.00*	0.00	-0.00	0.00	-0.00	0.00	0.00*	-0.00	0.00
	(-0.28)	(1.83)	(0.38)	(-1.15)	(0.63)	(-0.80)	(0.69)	(1.88)	(-0.40)	(0.21)
ILQ	0.00	-0.01***	0.00	-0.00	-0.00***	0.00	-0.00	-0.00	-0.00	-0.00
	(0.20)	(-3.15)	(0.78)	(-0.98)	(-2.60)	(0.72)	(-0.34)	(-0.86)	(-0.35)	(-1.51)
$VOLDEV$	-0.00	0.01**	-0.01**	-0.00	-0.01**	0.01***	0.01***	0.00**	-0.00	-0.00**
	(-0.54)	(2.04)	(-2.39)	(-0.74)	(-2.48)	(3.22)	(3.21)	(2.05)	(-0.55)	(-2.21)
R^2_{adj}	76.21%	62.62%	51.75%	21.25%	34.95%	48.63%	28.77%	32.40%	29.84%	25.16%
No. Obs.	210	210	210	210	210	210	210	210	210	210

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. The observable factors include 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.

Figure B2: Common factors (F^C) *vs.* principal components (PC) of observable factors (top panel: correlations; bottom panel: plots)



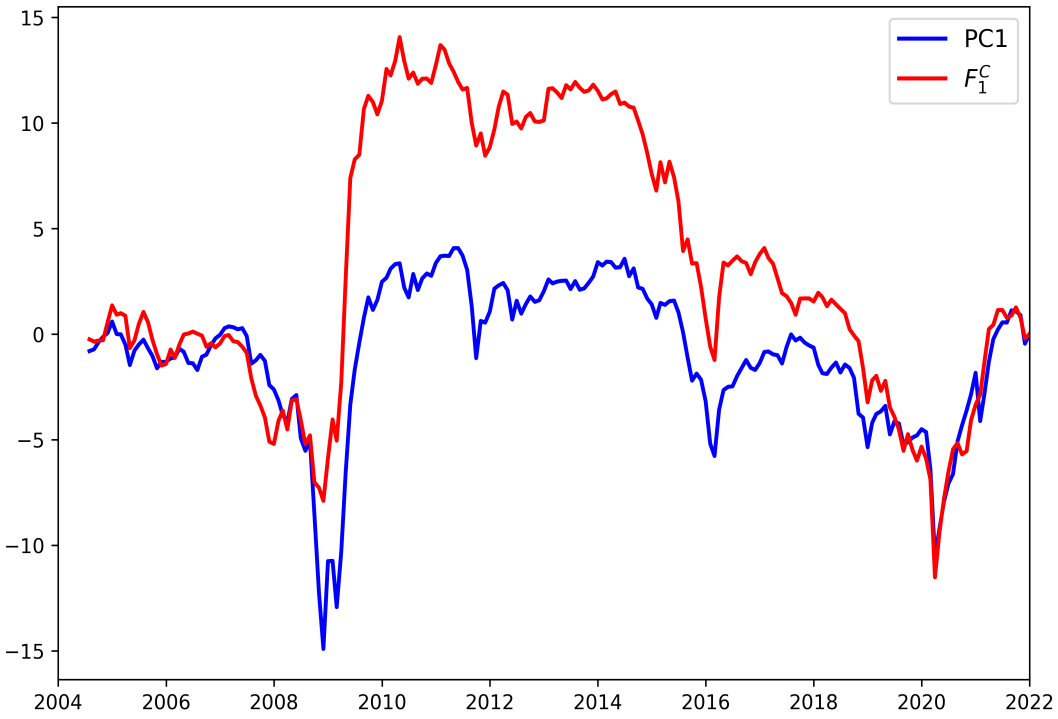


Table B3: Correlations between common and asset-class-specific factors[†]

Factors	F_1^s	F_2^s	F_3^s	F_4^s	F_5^s	F_6^s	F_7^s	F_8^s	F_9^s	F_{10}^s
F_1^C	0.80***	0.34***	-0.07	-0.18**	-0.00	0.05	0.02	-0.06	-0.00	0.03
F_2^C	-0.45***	0.63***	-0.10	0.01	0.10	0.12*	0.07	-0.11*	0.01	0.14**
F_3^C	-0.11*	-0.25***	-0.41***	0.04	-0.12*	0.14**	0.07	-0.27***	-0.16**	-0.05
F_4^C	0.35***	-0.10	-0.20***	0.45***	0.00	0.06	0.18***	-0.07	-0.07	0.09
F_5^C	0.06	-0.19***	0.45***	0.12*	0.20***	-0.01	-0.19***	0.09	-0.06	-0.02
F_6^C	0.04	-0.38***	0.19***	-0.13*	0.35***	0.16**	-0.01	-0.24***	0.06	0.21***
F_7^C	0.04	0.22***	0.51***	0.05	-0.33***	0.05	-0.08	-0.19***	-0.02	-0.04
F_8^C	0.03	-0.14**	-0.47***	-0.25***	-0.06	-0.09	-0.30***	0.09	0.13*	-0.04
F_9^C	-0.03	0.07	-0.12*	0.07	0.16**	-0.05	-0.03	0.03	-0.17**	0.01
F_{10}^C	-0.08	-0.33***	0.17**	-0.25***	-0.37***	0.07	0.27***	0.01	-0.11	0.02
Factors	F_1^b	F_2^b	F_3^b	F_4^b	F_5^b	F_6^b	F_7^b	F_8^b	F_9^b	F_{10}^b
F_1^C	0.91***	0.16**	0.02	0.07	-0.00	-0.02	0.04	-0.02	0.02	0.02
F_2^C	0.02	0.41***	0.28***	-0.13*	0.03	-0.11	-0.04	0.01	0.15**	0.03
F_3^C	0.16**	-0.69***	0.56***	0.02	0.02	0.01	-0.04	-0.08	-0.02	0.07
F_4^C	-0.33***	0.36***	0.46***	0.28***	0.01	-0.09	-0.00	-0.10	-0.06	0.09
F_5^C	-0.05	-0.20***	-0.30***	-0.26***	0.04	-0.30***	-0.13*	-0.16**	0.01	0.02
F_6^C	-0.09	-0.03	0.19***	-0.60***	-0.11	0.16**	0.06	0.13*	-0.00	-0.03
F_7^C	-0.10	-0.31***	-0.05	0.44***	-0.05	-0.25***	0.04	0.23***	0.16**	0.08
F_8^C	-0.10	-0.10	-0.41***	0.22***	-0.04	0.30***	0.22***	-0.17**	0.09	0.03
F_9^C	-0.01	-0.01	-0.15**	0.14**	0.25***	0.01	-0.34***	0.05	-0.14**	0.01
F_{10}^C	0.07	0.16**	0.08	0.39***	-0.03	0.25***	-0.08	0.04	-0.09	-0.03
Factors	F_1^o	F_2^o	F_3^o	F_4^o	F_5^o	F_6^o	F_7^o	F_8^o	F_9^o	F_{10}^o
F_1^C	0.53***	-0.25***	-0.10	0.04	0.12*	0.02	0.03	0.17**	0.09	0.05
F_2^C	0.67***	0.06	0.00	-0.13*	-0.05	-0.00	0.02	-0.17**	0.07	0.07
F_3^C	0.13*	0.30***	0.59***	0.05	-0.26***	0.02	-0.02	0.05	-0.18**	0.09
F_4^C	0.18***	0.24***	0.31***	0.05	0.21***	0.10	-0.09	-0.04	-0.03	-0.10
F_5^C	0.31***	0.63***	-0.35***	0.17**	0.03	-0.05	0.00	0.05	-0.11	-0.10
F_6^C	0.21***	-0.53***	-0.00	0.23***	-0.17**	-0.03	-0.16**	0.04	-0.30***	-0.08
F_7^C	0.14**	-0.28***	0.26***	-0.10	0.09	0.06	0.08	-0.14**	0.04	-0.08
F_8^C	0.25***	-0.11	-0.07	-0.21***	-0.16**	-0.12*	0.16**	0.02	0.07	-0.05
F_9^C	0.02	-0.07	0.12*	0.86***	0.10	-0.07	0.11	-0.05	0.16**	0.06
F_{10}^C	0.06	0.03	-0.15**	0.11	-0.16**	0.07	-0.37***	-0.01	0.10	0.07

[†] ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. F^C denotes common factors; F^X for $X \in \{s, b, o\}$ denotes asset-class-specific regressed-PCA factors for stock, corporate bond, and option markets, respectively.

Figure B3: Estimates of coefficients B for the first common factor with 95% confidence intervals

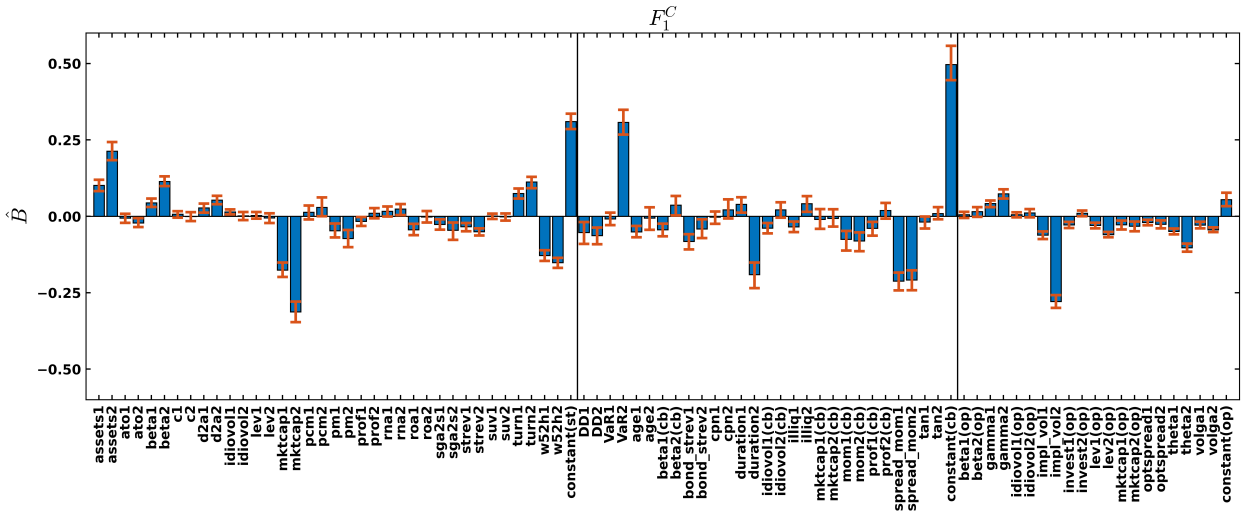


Table B4: Contribution of asset-class-specific constituents to the common factors†

	F_s^C	F_b^C	F_o^C
F_1^C	0.85	0.92	0.59
	[0.38]	[0.51]	[0.12]
F_2^C	0.71	0.53	0.68
	[0.47]	[0.15]	[0.39]
F_3^C	0.51	0.86	0.68
	[0.17]	[0.60]	[0.23]
F_4^C	0.47	0.63	0.44
	[0.33]	[0.53]	[0.14]
F_5^C	0.53	0.49	0.77
	[0.22]	[0.19]	[0.60]
F_6^C	0.55	0.61	0.63
	[0.25]	[0.32]	[0.43]
F_7^C	0.62	0.55	0.42
	[0.39]	[0.39]	[0.22]
F_8^C	0.58	0.52	0.36
	[0.36]	[0.40]	[0.24]
F_9^C	0.25	0.43	0.89
	[0.07]	[0.17]	[0.77]
F_{10}^C	0.53	0.45	0.37
	[0.49]	[0.37]	[0.14]

† For each common factor, the first row shows its correlations with associated asset-class-specific constituents; the second row shows its variance decomposition in square brackets, defined as $\frac{\text{Cov}(F_X^C, F^C)}{\text{Var}(F^C)}$ for $X \in \{s, b, o\}$.

Table B5: Correlations between common factors and macroeconomic and financial variables†

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
Core inflation	-0.04	-0.14*	-0.11	-0.19***	0.03	0.09	0.01	-0.04	0.08	0.15**
Δc	0.13*	-0.02	0.06	-0.34***	0.08	-0.06	-0.19***	0.19***	0.16**	0.09
ΔIP	-0.04	-0.11	0.02	-0.30***	0.10	-0.04	-0.19***	0.10	0.01	0.09
$\Delta(FFR)$	0.09	-0.08	-0.30***	-0.18***	-0.04	-0.10	-0.10	0.15**	-0.04	0.22***
$\Delta(TERM)$	0.25***	-0.26***	0.21***	-0.15**	-0.01	-0.09	0.38***	0.21***	-0.04	-0.01
$\Delta(DEF)$	-0.27***	-0.05	-0.02	0.01	-0.02	-0.01	0.14*	0.14**	0.12*	0.14**
$\Delta(VIX)$	-0.44***	-0.34***	0.18***	0.12*	0.13*	-0.19***	0.14*	-0.12*	0.01	-0.07
$\Delta(EPU)$	-0.32***	-0.02	0.01	0.28***	-0.02	0.06	0.26***	-0.01	-0.22***	-0.04
$\Delta(FINU)$	-0.48***	-0.22***	0.09	-0.06	-0.07	0.06	0.24***	-0.03	-0.22***	-0.16**
$\Delta(MACU)$	-0.37***	-0.01	0.21***	0.13*	0.05	0.00	0.23***	0.11	-0.17**	-0.24***
HKM	0.54***	-0.08	-0.18**	-0.19***	-0.17**	0.01	-0.12*	0.30***	-0.03	0.14**
LIQ	0.16**	0.03	-0.19***	-0.07	0.15**	-0.16**	-0.15**	-0.07	-0.15**	0.07

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. See Section 4.2 for details on the macroeconomic and financial variables.

Table B6: Regression of common factors on macroeconomic and financial variables†

Factor	F_1^C	F_2^C	F_3^C	F_4^C	F_5^C	F_6^C	F_7^C	F_8^C	F_9^C	F_{10}^C
Core inflation	-3.26	-7.09	-5.84	-4.29	6.16	5.61	6.40	-4.63	5.87**	4.87
	(-0.51)	(-0.82)	(-1.18)	(-0.78)	(1.12)	(0.76)	(1.15)	(-0.95)	(2.37)	(1.36)
	[0.01]	[0.04]	[0.04]	[0.05]	[0.02]	[0.07]	[0.02]	[0.02]	[0.03]	[0.09]
Δc	3.92***	2.04*	1.02	-1.38	0.42	-0.26	-0.41	1.30*	1.10	0.03
	(3.05)	(1.69)	(0.69)	(-1.05)	(0.40)	(-0.16)	(-0.47)	(1.75)	(1.50)	(0.04)
	[0.03]	[0.02]	[0.05]	[0.18]	[0.03]	[0.01]	[0.04]	[0.12]	[0.09]	[0.02]
ΔIP	-4.45***	-1.27	0.73	-0.93	0.20	0.65	-0.91	0.66	-1.22*	-0.12
	(-3.45)	(-1.12)	(0.42)	(-0.66)	(0.14)	(0.80)	(-1.33)	(0.86)	(-1.70)	(-0.23)
	[0.04]	[0.04]	[0.03]	[0.14]	[0.05]	[0.02]	[0.06]	[0.05]	[0.06]	[0.02]
$\Delta(FFR)$	-0.11	-0.05	-0.18	-0.06	-0.02	-0.07	0.10*	0.06	-0.07**	0.05
	(-1.24)	(-0.93)	(-1.46)	(-1.07)	(-0.41)	(-0.89)	(1.89)	(0.96)	(-2.29)	(1.63)
	[0.01]	[0.03]	[0.32]	[0.04]	[0.03]	[0.08]	[0.03]	[0.07]	[0.06]	[0.17]
$\Delta(TERM)$	0.28***	-0.16***	0.09*	-0.14***	0.03	-0.07	0.23***	0.06*	-0.02	0.02
	(3.97)	(-2.98)	(1.65)	(-3.17)	(0.48)	(-0.94)	(4.08)	(1.77)	(-0.53)	(0.53)
	[0.12]	[0.21]	[0.14]	[0.12]	[0.01]	[0.09]	[0.52]	[0.13]	[0.01]	[0.01]
$\Delta(DEF)$	-0.00**	-0.00	-0.00	-0.00*	-0.00	-0.00	0.00	0.00	0.00*	0.00**
	(-2.56)	(-0.32)	(-0.30)	(-1.92)	(-0.13)	(-0.21)	(0.96)	(1.44)	(1.94)	(2.38)
	[0.06]	[0.01]	[0.01]	[0.02]	[0.00]	[0.00]	[0.02]	[0.07]	[0.14]	[0.22]
$\Delta(VIX)$	-0.00	-0.01***	0.00	0.01***	0.00	-0.01**	-0.00	-0.00	0.00*	0.00
	(-0.86)	(-4.64)	(0.94)	(3.47)	(1.17)	(-2.21)	(-0.90)	(-1.33)	(1.77)	(0.23)
	[0.13]	[0.41]	[0.07]	[0.10]	[0.13]	[0.38]	[0.02]	[0.06]	[0.03]	[0.01]
$\Delta(EPU)$	-0.00	0.00	-0.00	0.00**	-0.00	0.00	0.00	0.00	-0.00***	0.00
	(-0.38)	(0.24)	(-0.81)	(2.56)	(-0.10)	(0.37)	(0.65)	(1.07)	(-2.60)	(0.50)
	[0.06]	[0.00]	[0.02]	[0.14]	[0.01]	[0.02]	[0.08]	[0.02]	[0.19]	[0.02]
$\Delta(FINU)$	-1.14***	-0.37	-0.27	-0.90***	-0.69**	0.45	0.27	-0.01	-0.42***	-0.13
	(-2.61)	(-1.34)	(-1.13)	(-3.35)	(-2.25)	(1.56)	(1.46)	(-0.06)	(-3.02)	(-1.07)
	[0.18]	[0.11]	[0.02]	[0.13]	[0.19]	[0.10]	[0.08]	[0.01]	[0.18]	[0.09]
$\Delta(MACU)$	-1.45**	0.49	0.70	0.18	0.59	-0.13	0.12	0.73**	-0.35	-0.51**
	(-2.38)	(1.11)	(0.96)	(0.36)	(0.95)	(-0.43)	(0.58)	(2.14)	(-1.21)	(-2.38)
	[0.10]	[0.02]	[0.12]	[0.02]	[0.07]	[0.01]	[0.05]	[0.13]	[0.08]	[0.27]
HKM	0.92***	-0.49**	-0.11	0.04	-0.28*	0.01	-0.29***	0.33***	-0.07	0.04
	(2.94)	(-2.41)	(-0.35)	(0.25)	(-1.69)	(0.07)	(-2.92)	(2.72)	(-0.56)	(0.40)
	[0.26]	[0.11]	[0.07]	[0.05]	[0.23]	[0.02]	[0.06]	[0.30]	[0.02]	[0.06]
LIQ	0.41	0.04	-0.26	-0.08	0.33***	-0.31	0.01	-0.12	-0.16**	0.05
	(1.52)	(0.21)	(-1.57)	(-0.63)	(2.68)	(-1.56)	(0.11)	(-1.17)	(-1.97)	(0.77)
	[0.02]	[0.00]	[0.11]	[0.01]	[0.23]	[0.21]	[0.02]	[0.03]	[0.10]	[0.01]
R^2_{adj}	49.45%	21.18%	14.66%	21.28%	6.05%	7.90%	23.28%	19.81%	17.61%	7.91%

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. The Shapley-Owen R^2's are in square brackets. Common factors, macroeconomic and financial variables are standardized using the time-series standard deviation. See Section 4.2 for details on macroeconomic and financial variables.

Table B7: Regression for the asset-class-specific components of the first common factor on macroeconomic and financial variables†

	$\widehat{F}_s^C$	$\widehat{F}_b^C$	$\widehat{F}_o^C$
Core inflation	13.18	-28.70	-19.68
	(0.29)	(-1.02)	(-0.48)
Δc	-1.23	19.65**	28.08***
	(-0.13)	(2.22)	(4.40)
ΔIP	-13.42*	-20.86***	-20.94***
	(-1.72)	(-2.99)	(-3.59)
$\Delta(FFR)$	-0.26	-0.47	-0.76
	(-0.56)	(-1.10)	(-1.60)
$\Delta(TERM)$	1.18***	1.41***	0.97***
	(2.99)	(3.71)	(3.04)
$\Delta(DEF)$	-0.00**	-0.00**	-0.00
	(-2.36)	(-2.12)	(-1.56)
$\Delta(VIX)$	0.03	-0.01	-0.05***
	(1.62)	(-0.59)	(-3.23)
$\Delta(EPU)$	0.00	-0.00	-0.00
	(0.54)	(-1.27)	(-0.63)
$\Delta(FINU)$	-5.34***	-5.09**	-4.42**
	(-2.84)	(-2.01)	(-2.16)
$\Delta(MACU)$	-5.02*	-6.24*	-7.13***
	(-1.66)	(-1.79)	(-2.84)
HKM	5.53***	4.34**	2.02
	(3.62)	(2.30)	(1.55)
LIQ	1.52	1.73*	1.72
	(1.17)	(1.80)	(1.05)
R^2_{adj}	25.81%	45.44%	48.46%

† ***: p-value< 1%; **: p-value< 5%; *: p-value< 10%. t-statistics are reported in parentheses using Newey-West standard errors with four period lags. Common factors, macroeconomic and financial variables are standardized using the time-series standard deviation See Section 4.2 for details on macroeconomic and financial variables.

Table B8: Forecasting and nowcasting of macro-financial variables with ten common factors

	Panel I: Forecast			Panel II: Nowcast		
	β^Y	t	R^2 (%)	β^Y	t	R^2 (%)
Core inflation	1.87***	(5.67)	17.83	0.13	(0.66)	0.30
$\Delta(FFR)$	0.11	(1.05)	0.73	0.06	(0.61)	0.25
Δc	0.66*	(1.97)	2.55	-0.82	(-1.36)	1.23
ΔIP	0.85***	(5.32)	16.06	0.11	(0.49)	0.16
$\Delta(MACU)$	-0.39*	(-1.84)	2.23	0.54***	(2.62)	4.39
$\Delta(DEF)$	-0.45*	(-1.90)	2.39	0.11	(0.93)	0.58
$\Delta(TERM)$	0.17	(1.00)	0.67	0.51***	(6.35)	21.29
$\Delta(FINU)$	0.22**	(2.11)	2.93	0.82***	(6.99)	24.72
LIQ	-0.28**	(-2.06)	2.78	0.23**	(2.37)	3.64
$\Delta(VIX)$	0.08	(0.96)	0.62	1.03***	(10.41)	42.10
$\Delta(EPU)$	0.19	(1.49)	1.48	0.70***	(3.21)	6.47
HKM	0.10	(1.19)	0.95	0.76***	(10.46)	42.34

† Panel I and II tabulate the forecasting and nowcasting regression coefficients in Section 4.2.2, respectively.

Table B9: Sharpe ratios of the common and asset-class-specific factors[†]

I: Common factors										
	1	2	3	4	5	6	7	8	9	10
In Sample	**0.86**	**1.11**	**0.75**	**1.63**	**1.42**	**0.51**	0.31	0.22	**1.78**	**0.51**
- Stocks	**0.59**	**-0.50**	-0.41	**0.71**	0.35	0.40	0.10	-0.22	-0.19	-0.44
- Corporate Bond	0.38	**0.64**	0.07	0.13	**-0.88**	-0.20	-0.38	**-0.58**	-0.42	**0.64**
- Option	**2.00**	**2.23**	**2.46**	**3.17**	**2.10**	**0.63**	**0.99**	**1.20**	**2.34**	**1.06**
Out of Sample	**0.81**	**0.79**	**1.17**	-0.22	**0.83**	**1.76**	-0.05	**1.25**	**0.64**	**0.96**
- Stocks	0.20	-0.09	-0.15	-0.55	-0.28	0.60	0.40	0.50	0.31	0.09
- Corporate Bond	0.17	**-0.69**	**0.70**	0.07	**-0.71**	0.37	-0.33	0.05	**-1.04**	0.07
- Option	**2.21**	**2.18**	**1.67**	0.17	**1.20**	**1.80**	-0.46	**1.13**	**1.42**	**1.17**

II: Stock factors										
	1	2	3	4	5	6	7	8	9	10
In Sample	**0.61**	0.00	0.10	**0.55**	**0.63**	**0.59**	**0.50**	0.20	**0.50**	**1.32**
Out of Sample	0.25	-0.32	0.18	-0.14	0.52	**0.78**	**1.05**	-0.11	0.15	0.60

III: Corporate bond factors										
	1	2	3	4	5	6	7	8	9	10
In Sample	0.34	0.45	**0.57**	0.25	0.19	0.12	**0.52**	0.32	0.02	0.27
Out of Sample	0.09	-0.15	-0.43	0.38	-0.01	0.24	0.06	-0.04	-0.13	-0.39

IV: Option factors										
	1	2	3	4	5	6	7	8	9	10
In Sample	**2.34**	**1.08**	**1.43**	**2.05**	**1.36**	**0.77**	**0.49**	**1.50**	0.27	**0.56**
Out of Sample	**2.20**	0.61	**0.93**	0.28	-0.15	0.53	**0.94**	**1.04**	**1.05**	**0.88**

[†] Panel I reports the in-sample and out-of-sample annualized Sharpe ratios of common factors and their asset-class-specific components. Panel I-IV report the annualized Sharpe ratios of the asset-class-specific factors.

Table B10: In-sample and out-of-sample performance (R^2) of the common factors[†]

I: All asset returns

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	24.41	8.11	2.96	7.92	4.52
2	35.12	10.15	3.56	9.87	5.43
3	42.83	11.41	4.00	13.16	6.21
4	50.76	12.09	4.49	12.58	6.79
5	56.96	13.01	4.54	11.98	6.85
6	61.70	14.43	4.79	13.15	7.27
7	65.47	15.23	4.98	12.66	7.57
8	68.78	16.30	5.02	11.14	7.59
9	72.05	17.14	5.25	11.98	7.99
10	74.38	17.88	5.41	12.57	8.24
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.22	0.83	0.37	24.67	

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	23.64	7.24	8.82	11.19	7.37
2	37.62	7.62	9.78	11.62	8.40
3	41.11	8.26	10.28	12.11	8.86
4	49.56	8.73	10.91	13.17	9.49
5	54.04	9.26	11.03	13.15	9.58
6	56.79	9.57	11.45	13.68	9.96
7	61.76	10.38	11.91	13.86	10.34
8	65.88	11.52	11.82	13.63	10.24
9	66.28	11.60	12.02	14.20	10.48
10	68.90	11.98	12.39	14.75	10.89
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.23	0.44	0.03	18.75	

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	25.95	18.96	5.13	−20.06	−4.91
2	30.84	23.10	4.40	−27.40	−7.27
3	44.56	28.36	5.01	−25.77	−5.73
4	53.18	30.42	9.98	−16.04	−0.25
5	57.33	31.89	10.76	−15.83	0.08
6	62.57	32.24	15.87	−10.63	6.18
7	66.03	36.38	19.01	−7.28	8.38
8	69.91	37.72	18.48	−7.71	7.90
9	70.91	38.07	21.92	−5.58	12.27
10	74.91	38.81	21.99	−7.61	11.93
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	1.99	−0.22	1.22	48.57	

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	23.74	7.66	1.47	8.25	2.84
2	36.71	10.94	2.01	10.37	3.92
3	42.70	12.33	2.43	13.74	4.95
4	49.70	13.03	2.78	12.97	5.00
5	58.75	14.23	2.79	12.35	4.99
6	64.51	16.77	2.86	13.47	5.18
7	67.66	17.19	2.91	12.92	5.25
8	69.96	18.17	3.01	11.35	5.33
9	77.05	19.73	3.15	12.18	5.65
10	77.87	20.81	3.26	12.81	5.80
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.17	0.85	0.57	27.28	

[†]K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table B11: Out-of-sample performance of the pure-*alpha* strategy[†]

I: Pure-*alpha* portfolios			
K	μ_α	σ_α	SR_α
1	9.02	3.75	2.41
2	8.18	3.31	2.47
3	7.81	3.29	2.37
4	7.98	3.26	2.45
5	6.69	2.55	2.62
6	4.47	1.84	2.43
7	4.51	1.69	2.67
8	4.04	1.60	2.53
9	3.78	1.39	2.72
10	3.51	1.36	2.58

II: Stock components			
K	μ_α	σ_α	SR_α
1	0.57	0.54	1.05
2	0.67	0.93	0.73
3	0.75	1.01	0.74
4	0.98	1.14	0.86
5	1.12	1.01	1.12
6	0.81	0.74	1.11
7	0.66	0.48	1.37
8	0.57	0.47	1.23
9	0.53	0.50	1.05
10	0.50	0.50	1.01

III: Corporate bond components			
K	μ_α	σ_α	SR_α
1	−0.28	1.08	−0.26
2	−0.07	1.08	−0.06
3	−0.18	1.13	−0.16
4	−0.15	0.96	−0.16
5	0.14	0.95	0.15
6	−0.23	0.46	−0.51
7	−0.17	0.49	−0.35
8	−0.21	0.47	−0.45
9	0.15	0.46	0.33
10	0.13	0.43	0.30

IV: Option components			
K	μ_α	σ_α	SR_α
1	8.73	3.57	2.45
2	7.57	3.12	2.43
3	7.24	3.05	2.37
4	7.16	3.02	2.37
5	5.42	2.27	2.39
6	3.89	1.71	2.28
7	4.02	1.65	2.44
8	3.68	1.54	2.39
9	3.11	1.37	2.27
10	2.89	1.26	2.29

[†]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* portfolios and their associated components in (5.6).

Figure B4: Estimates of coefficients a with 95% confidence intervals ($K = 10$)

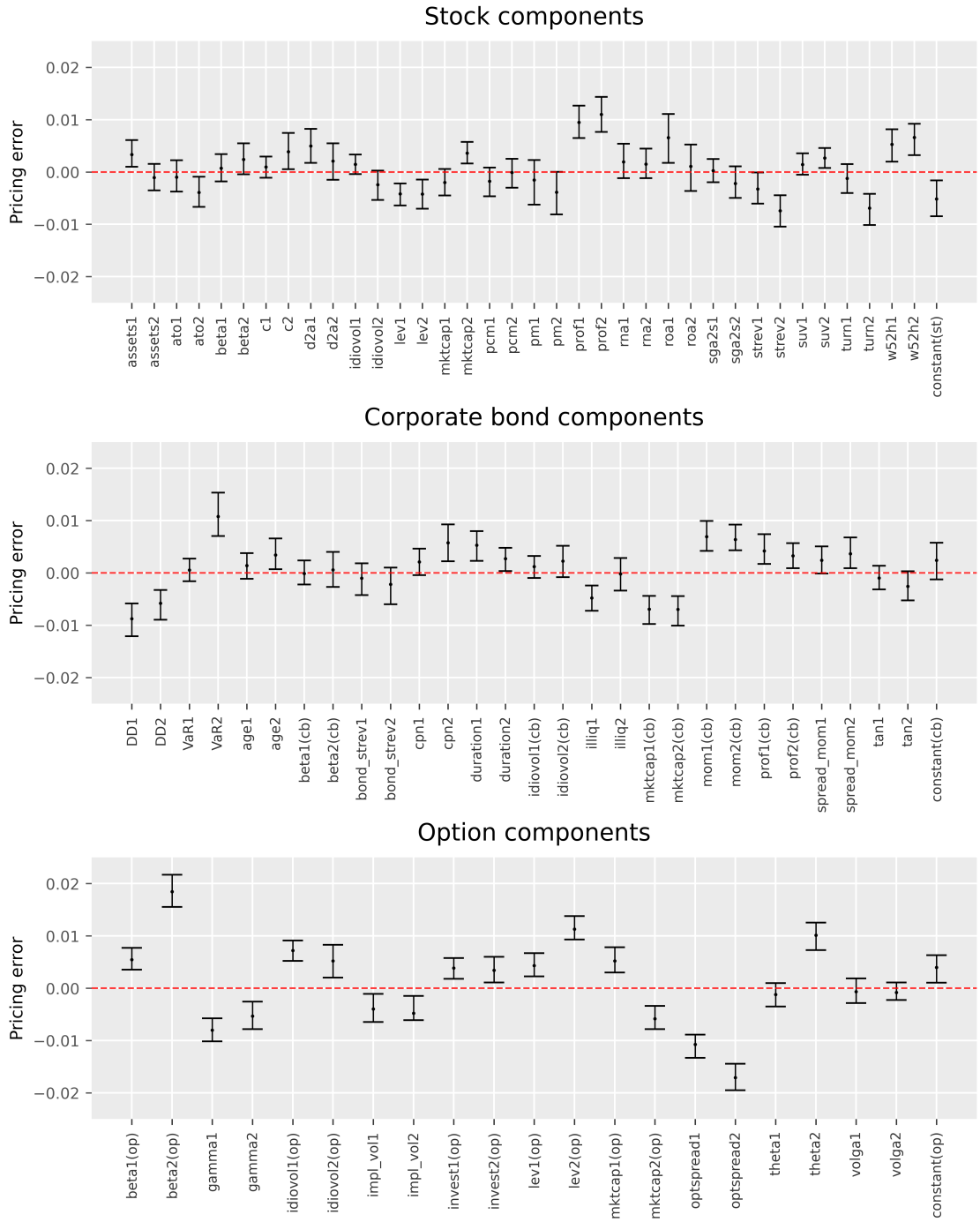


Table B12: In-sample Sharpe ratios of MVE portfolio and its constituents and their correlations with common factors†

I: Sharpe ratios				
	Joint	Stock	CorpBond	Option
Joint MVE/constituents	4.30	2.17	1.00	1.97
Mean	5.37	2.37	0.60	2.40
Std	4.32	3.78	2.09	4.21
Asset-class MVE	-	3.08	0.36	3.42
Mean	-	0.84	0.23	1.32
Std	-	0.95	2.18	1.34

II: Correlations between constituents				
	Joint	Stock	CorpBond	Option
Joint	-	0.55***	0.17**	0.45***
Stock	-	-	0.08	-0.38***
Corpbond	-	-	-	-0.40***

III: Correlations with common factors				
	Joint	Stock	CorpBond	Option
F_1^C	-0.16**	-0.11	0.38***	-0.26***
F_2^C	0.14**	0.07	0.20***	-0.02
F_3^C	-0.09	-0.13*	-0.34***	0.19***
F_4^C	-0.08	-0.27***	-0.07	0.19***
F_5^C	0.14**	0.15**	-0.06	0.05
F_6^C	-0.01	0.16**	-0.01	-0.15**
F_7^C	-0.04	-0.05	-0.33***	0.16**
F_8^C	0.03	0.08	-0.04	-0.02
F_9^C	0.02	-0.12*	-0.10	0.18***
F_{10}^C	0.16**	0.43***	0.02	-0.23***

† The joint MVE portfolio is constructed with $K = 10$, where its constituents is defined in (6.5). Panel (I) shows the Sharpe ratios of the joint MVE portfolio, its constituents, and the asset-class-specific MVE portfolios. Panel (II) reports correlations among the constituents in the joint MVE portfolio. Panel (III) reports correlations between the constituents of the joint MVE portfolio and the common factors.

Figure B5: Out-of-sample Sharpe ratios of joint and asset-class-specific MVE portfolios

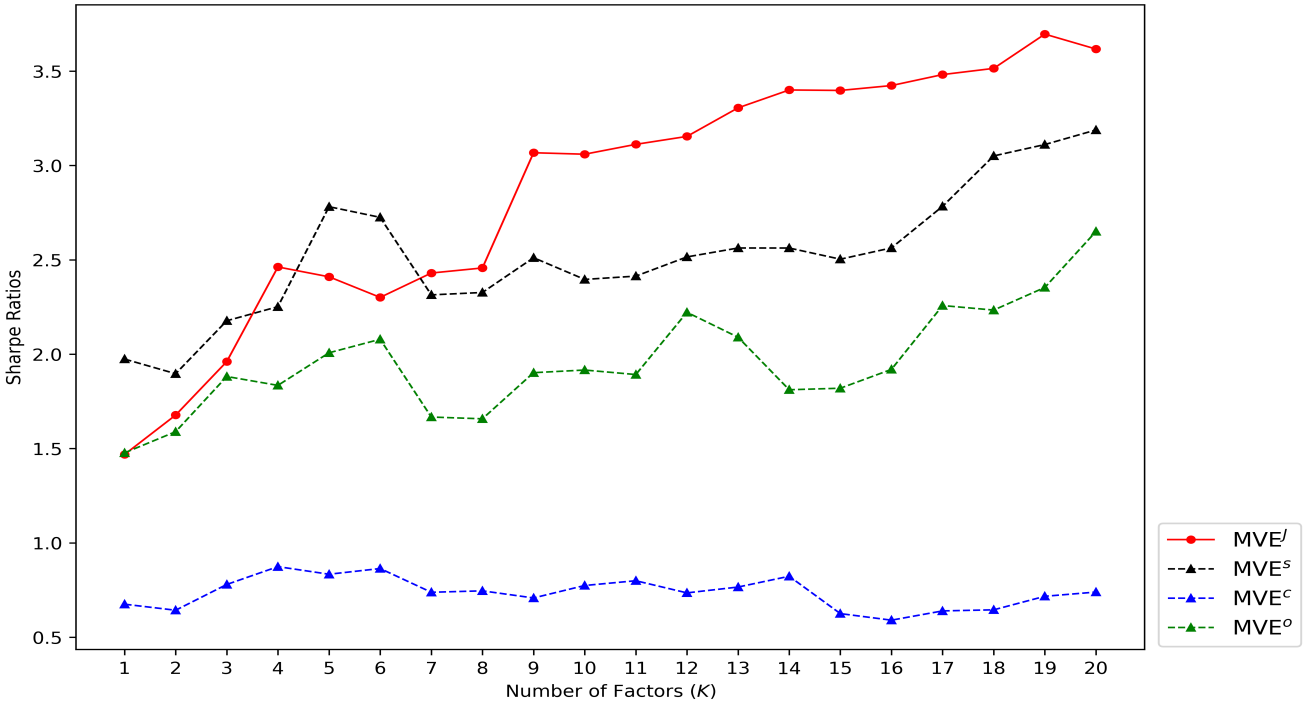


Table B13: Market distances based on common and pairwise factors[†]

K	$d(\mathcal{M}^s,\mathcal{M}^b)$	p	$d(\mathcal{M}^s,\mathcal{M}^o)$	p	$d(\mathcal{M}^b,\mathcal{M}^o)$	p	$d(\widetilde{\mathcal{M}}^s,\widetilde{\mathcal{M}}^b)$	p	$d(\widetilde{\mathcal{M}}^s,\widetilde{\mathcal{M}}^o)$	p	$d(\widetilde{\mathcal{M}}^b,\widetilde{\mathcal{M}}^o)$	p
I: Distance based on common factors: $\boldsymbol{F}^C$												
1	0.46	0.46	3.35	0.29	6.30	0.11	1.11	0.53	5.81	0.32	12.00	0.05
2	0.75	0.63	13.67	0.10	13.43	0.06	1.18	0.80	11.73	0.35	16.69	0.09
3	0.81	0.80	34.58	0.03	32.29	0.01	1.55	0.90	38.30	0.13	37.36	0.02
4	1.80	0.66	38.33	0.04	40.89	0.01	3.14	0.87	44.87	0.15	51.97	0.01
5	4.70	0.29	46.18	0.03	61.20	0.00	11.35	0.47	50.41	0.14	79.23	0.00
6	10.35	0.07	50.94	0.02	61.24	0.00	28.95	0.17	67.17	0.09	79.24	0.00
7	10.35	0.11	51.88	0.03	62.31	0.00	29.78	0.22	67.27	0.12	79.60	0.00
8	10.42	0.15	56.68	0.04	66.01	0.00	32.57	0.25	82.27	0.09	84.44	0.01
9	11.25	0.16	88.69	0.01	109.17	0.00	34.19	0.27	120.90	0.03	140.52	0.00
10	11.28	0.20	94.64	0.01	116.01	0.00	34.48	0.30	124.27	0.03	146.14	0.00
II: Distance based on pairwise factors: F^{sb}, F^{so}, F^{bo}												
1	0.23	0.60	4.50	0.14	8.14	0.08	0.53	0.65	7.71	0.14	12.29	0.06
2	3.25	0.14	25.75	0.01	23.88	0.01	4.00	0.45	24.56	0.09	30.11	0.01
3	3.63	0.17	48.30	0.00	49.57	0.00	4.95	0.53	59.23	0.02	57.11	0.00
4	3.88	0.26	52.70	0.01	57.15	0.00	6.04	0.61	68.64	0.03	70.70	0.00
5	7.79	0.12	52.73	0.01	59.56	0.00	28.37	0.15	70.52	0.04	71.31	0.00
6	8.08	0.14	55.72	0.02	64.44	0.00	29.04	0.18	70.69	0.07	73.96	0.00
7	8.17	0.20	72.32	0.01	102.93	0.00	29.15	0.21	90.24	0.05	126.11	0.00
8	9.48	0.17	72.45	0.01	109.32	0.00	31.28	0.20	90.47	0.07	133.94	0.00
9	13.04	0.07	88.94	0.01	112.03	0.00	37.89	0.17	121.28	0.03	134.77	0.00
10	19.94	0.01	88.95	0.01	113.01	0.00	45.16	0.13	122.29	0.03	135.45	0.00

[†] K denotes the number of factors. $d(\mathcal{M}^A,\mathcal{M}^B)$ for $A,B\in\{s,b,o\}$ denotes the market distances of different pairs based on SDFs constructed as in (7.4); $d(\widetilde{\mathcal{M}}^A,\widetilde{\mathcal{M}}^B)$ for $A,B\in\{s,b,o\}$ denotes the market distances based on the SDFs constructed with managed portfolios. The associated p-values are also reported. The left part of each panel is with SDFs constructed as in (7.4) in the span of individual asset excess returns; the right part is with SDFs in the span of managed portfolio return spaces with $M_{t+1}=1-\boldsymbol{b}_t'(\tilde{R}_{t+1}-E_t[\tilde{R}_{t+1}])$ and $\boldsymbol{b}_t=\mathrm{Var}_t^{-1}[\tilde{\boldsymbol{R}}_{t+1}]E_t[\tilde{\boldsymbol{R}}_{t+1}]$.

Table B14: Market segmentation based on regression approach with common and pairwise factors†

K	δ^C_{s-b}	δ^C_{s-o}	δ^C_{b-o}	δ^{sb}_{s}	δ^{sb}_{b}	δ^{sb}_{s-b}	δ^{so}_{s}	δ^{so}_{o}	δ^{so}_{s-o}	δ^{bo}_{b}	δ^{bo}_{o}	δ^{o}_{b-o}
1	-0.18	3.82**	4.00**	0.64	0.75	-0.11	2.21***	-0.98	3.19**	2.88***	-0.73	3.60***
	(-0.17)	(2.23)	(2.39)	(0.89)	(1.30)	(-0.12)	(6.20)	(-0.63)	(2.25)	(7.98)	(-0.52)	(2.62)
2	1.05	4.22***	3.17***	-0.27	1.57**	-1.84**	5.09***	-0.30	5.39***	5.50***	0.81	4.68***
	(1.21)	(3.48)	(2.79)	(-0.66)	(2.19)	(-2.35)	(6.85)	(-0.35)	(4.95)	(9.79)	(0.82)	(4.87)
	[0.48]	[0.00]	[0.00]	[0.66]	[0.07]	[0.06]	[0.00]	[0.28]	[0.00]	[0.00]	[0.71]	[0.00]
3	-0.22	3.15***	3.37***	0.09	0.82*	-0.72	5.05***	-0.34	5.39***	3.67***	-0.88	4.55***
	(-0.29)	(2.98)	(3.78)	(0.11)	(1.96)	(-0.82)	(7.31)	(-0.74)	(6.53)	(10.93)	(-1.15)	(5.95)
	[0.67]	[0.00]	[0.00]	[0.12]	[0.00]	[0.12]	[0.00]	[0.07]	[0.00]	[0.00]	[0.71]	[0.00]
4	-1.18	2.63**	3.81***	-0.20	-0.30	0.10	0.49	1.58**	-1.09	2.65***	-0.23	2.88***
	(-1.54)	(2.26)	(3.62)	(-0.40)	(-0.90)	(0.16)	(1.23)	(2.13)	(-1.31)	(4.88)	(-0.45)	(4.28)
	[0.46]	[0.00]	[0.00]	[0.12]	[0.00]	[0.18]	[0.00]	[0.12]	[0.00]	[0.00]	[0.32]	[0.00]
5	-1.10	3.91***	5.01***	-1.06*	1.09***	-2.15***	2.23***	1.45*	0.78	-0.89**	-0.25	-0.64
	(-1.63)	(4.37)	(6.34)	(-1.87)	(4.90)	(-3.30)	(4.75)	(1.94)	(0.89)	(-2.35)	(-0.32)	(-0.87)
	[0.31]	[0.00]	[0.00]	[0.20]	[0.00]	[0.00]	[0.00]	[0.20]	[0.00]	[0.00]	[0.18]	[0.00]
6	-2.11***	-1.89**	0.22	-0.28	0.67	-0.94*	2.26***	0.79	1.46**	1.42***	-0.35	1.77**
	(-3.00)	(-2.35)	(0.25)	(-0.74)	(1.48)	(-1.92)	(5.42)	(1.45)	(2.14)	(4.52)	(-0.45)	(2.08)
	[0.00]	[0.00]	[0.00]	[0.22]	[0.00]	[0.00]	[0.00]	[0.30]	[0.00]	[0.00]	[0.24]	[0.00]
7	-0.23	0.19	0.41	0.59	0.15	0.44	2.23***	-0.82**	3.05***	4.48***	-0.64***	5.12***
	(-0.39)	(0.22)	(0.44)	(1.58)	(0.37)	(1.06)	(4.19)	(-2.32)	(5.13)	(9.68)	(-3.05)	(10.13)
	[0.00]	[0.00]	[0.00]	[0.14]	[0.00]	[0.00]	[0.00]	[0.29]	[0.00]	[0.00]	[0.01]	[0.00]
8	0.93*	2.06**	1.13	0.53	-0.12	0.65*	0.62*	0.02	0.61	1.39***	-0.26	1.65***
	(1.95)	(2.57)	(1.50)	(1.09)	(-1.05)	(1.68)	(1.68)	(0.05)	(1.15)	(4.09)	(-0.57)	(3.21)
	[0.00]	[0.00]	[0.00]	[0.20]	[0.00]	[0.00]	[0.00]	[0.13]	[0.00]	[0.00]	[0.01]	[0.00]
9	-0.70	4.42***	5.11***	-0.20	0.40	-0.60*	1.92***	-0.36	2.28***	0.99***	0.37	0.61
	(-1.41)	(7.64)	(9.69)	(-0.58)	(1.63)	(-1.73)	(6.73)	(-0.72)	(4.43)	(7.04)	(0.68)	(1.36)
	[0.00]	[0.00]	[0.00]	[0.07]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.01]	[0.00]
10	0.93**	0.39	-0.54	-0.33	0.66***	-1.00***	-0.25	-0.17	-0.08	0.99***	0.13	0.86*
	(2.15)	(0.53)	(-0.74)	(-0.93)	(3.48)	(-2.82)	(-1.26)	(-0.31)	(-0.13)	(3.48)	(0.27)	(1.70)
	[0.00]	[0.00]	[0.00]	[0.08]	[0.00]	[0.00]	[0.00]	[0.04]	[0.00]	[0.00]	[0.02]	[0.00]

† K denotes the number of factors. Based on the regressions in (7.7) for $X \in \{A, B\}$ and $A, B \in \{s, b, o\}$, δ^C_X and δ^{AB}_X are reported with t-statistics in parentheses and p-values for GRS-statistics in square brackets; $\delta^C_{A-B} = \delta^C_A - \delta^C_B$ and $\delta^{AB}_{A-B} = \delta^{AB}_A - \delta^{AB}_B$ are reported with t-statistics in parentheses and p-values for statistics of (7.8) in square brackets.

Table B15: Market segmentation based on regression approach with common and pairwise factors†

K	δ^C_{s-b}	δ^C_{s-o}	δ^C_{b-o}	δ^{sb}_s	δ^{sb}_b	δ^{sb}_{s-b}	δ^{so}_s	δ^{so}_o	δ^{so}_{s-o}	δ^{bo}_b	δ^{bo}_o	δ^o_{b-o}
1	-1.55	3.54**	5.08***	-0.17	0.83	-1.00	1.66***	-1.57	3.23**	2.81***	-1.58	4.39***
	(-1.41)	(2.05)	(3.06)	(-0.19)	(1.32)	(-0.94)	(3.76)	(-0.96)	(2.38)	(7.45)	(-1.11)	(3.26)
2	0.18	2.53*	2.35**	0.35	1.87**	-1.52*	4.10***	-0.13	4.22***	5.45***	1.14	4.32***
	(0.18)	(1.92)	(1.97)	(0.73)	(2.40)	(-1.73)	(4.41)	(-0.14)	(3.43)	(9.37)	(1.09)	(4.38)
	[0.36]	[0.01]	[0.00]	[0.74]	[0.03]	[0.16]	[0.00]	[0.17]	[0.00]	[0.00]	[0.51]	[0.00]
3	0.47	4.47***	4.00***	0.12	0.89*	-0.77	4.77***	-0.44	5.21***	3.71***	-1.12	4.82***
	(0.52)	(3.67)	(4.14)	(0.12)	(1.95)	(-0.76)	(5.39)	(-0.90)	(4.94)	(10.81)	(-1.38)	(5.73)
	[0.36]	[0.00]	[0.00]	[0.33]	[0.00]	[0.24]	[0.00]	[0.03]	[0.00]	[0.00]	[0.45]	[0.00]
4	-1.06	2.90**	3.96***	0.33	-0.36	0.70	0.17	2.03***	-1.86**	2.75***	-0.08	2.83***
	(-1.07)	(2.25)	(3.60)	(0.60)	(-1.03)	(1.19)	(0.36)	(2.69)	(-2.13)	(4.81)	(-0.15)	(4.23)
	[0.34]	[0.00]	[0.00]	[0.14]	[0.00]	[0.14]	[0.00]	[0.02]	[0.00]	[0.00]	[0.25]	[0.00]
5	-2.22**	2.59**	4.81***	-1.55**	1.23***	-2.78***	1.65***	1.50*	0.15	-0.75*	-0.36	-0.39
	(-2.54)	(2.48)	(6.01)	(-2.30)	(5.18)	(-3.59)	(2.86)	(1.95)	(0.18)	(-1.86)	(-0.44)	(-0.54)
	[0.03]	[0.00]	[0.00]	[0.22]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.22]	[0.00]
6	-2.82***	-2.28**	0.54	0.21	0.70	-0.49	2.47***	1.35**	1.12*	1.32***	0.07	1.25
	(-3.35)	(-2.45)	(0.65)	(0.52)	(1.47)	(-0.89)	(5.50)	(2.51)	(1.69)	(4.10)	(0.09)	(1.56)
	[0.00]	[0.00]	[0.00]	[0.28]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.32]	[0.00]
7	0.44	0.35	-0.08	0.34	0.20	0.14	1.92***	-0.98***	2.90***	4.73***	-0.46**	5.19***
	(0.65)	(0.38)	(-0.09)	(0.82)	(0.47)	(0.26)	(2.88)	(-2.70)	(4.26)	(9.98)	(-2.14)	(10.84)
	[0.00]	[0.00]	[0.00]	[0.23]	[0.00]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]	[0.03]	[0.00]
8	0.85	2.21**	1.36*	0.43	-0.15	0.57	0.33	0.10	0.23	1.48***	-0.21	1.69***
	(1.30)	(2.56)	(1.81)	(0.74)	(-1.22)	(1.29)	(0.76)	(0.24)	(0.41)	(4.39)	(-0.43)	(3.23)
	[0.00]	[0.00]	[0.00]	[0.30]	[0.00]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]	[0.03]	[0.00]
9	-1.04*	4.08***	5.12***	-0.55	0.43*	-0.98**	1.70***	-0.64	2.34***	1.07***	0.42	0.65
	(-1.68)	(6.10)	(10.23)	(-1.37)	(1.71)	(-2.29)	(4.86)	(-1.32)	(4.08)	(7.66)	(0.75)	(1.37)
	[0.00]	[0.00]	[0.00]	[0.18]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.05]	[0.00]
10	0.11	-0.48	-0.59	-0.26	0.67***	-0.93**	-0.06	-0.49	0.44	0.94***	0.26	0.68
	(0.22)	(-0.65)	(-0.86)	(-0.61)	(3.32)	(-2.25)	(-0.23)	(-0.87)	(0.81)	(3.23)	(0.50)	(1.27)
	[0.00]	[0.00]	[0.00]	[0.14]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.07]	[0.00]

† K denotes the number of factors. Based on the regressions in (7.7) for $X \in \{A, B\}$ and $A, B \in \{s, b, o\}$, δ^C_X and δ^{AB}_X are reported with t-statistics in parentheses and p-values for GRS-statistics in square brackets; $\delta^C_{A-B} = \delta^C_A - \delta^C_B$ and $\delta^{AB}_{A-B} = \delta^{AB}_A - \delta^{AB}_B$ are reported with t-statistics in parentheses and p-values for statistics of (7.8) in square brackets.

Table B16: Out-of-sample performance (R^2) of the common factors defined in (5.2)†

I: All asset returns			
K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	1.50	1.50	2.21
2	1.69	4.05	2.62
3	1.97	7.89	3.21
4	2.10	8.06	3.40
5	2.32	7.43	3.54
6	2.53	8.61	3.91
7	2.69	8.44	4.32
8	2.95	7.11	4.45
9	3.11	7.36	4.76
10	3.13	8.29	4.86
II: Stock returns			
K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	5.28	5.80	4.20
2	5.43	5.49	4.35
3	6.03	6.51	4.75
4	6.31	6.29	5.01
5	6.53	6.54	5.25
6	7.20	7.00	5.82
7	7.88	8.45	6.42
8	7.67	8.15	6.28
9	7.73	8.29	6.36
10	8.00	8.77	6.46
III: Corporate bond returns			
K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	9.46	−15.74	1.82
2	12.75	−10.15	3.25
3	14.73	−7.67	3.90
4	17.32	−3.90	5.72
5	16.76	−8.66	5.98
6	21.36	−6.28	9.84
7	22.10	−4.45	10.42
8	24.78	−1.81	14.11
9	25.40	−0.26	16.76
10	26.23	0.90	18.78
IV: Option returns			
K	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	0.37	1.67	0.76
2	0.48	4.23	1.23
3	0.64	8.16	1.81
4	0.67	8.28	1.74
5	0.91	7.69	1.75
6	0.89	8.88	1.82
7	0.90	8.64	2.00
8	1.22	7.22	2.24
9	1.39	7.46	2.61
10	1.33	8.40	2.51

†K: the number of factors specified; $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table B17: In-sample and out-of-sample performance of the factor models for each asset class[†]

I: Stock

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	39.89	5.27	9.81	10.76	8.51
2	54.70	7.24	10.07	11.18	8.77
3	66.64	8.73	11.72	13.69	10.36
4	71.77	12.86	13.24	16.17	11.78
5	76.10	14.01	13.59	16.34	12.08
6	79.34	14.47	13.76	16.29	12.26
7	82.10	14.79	14.05	16.94	12.56
8	84.68	14.98	14.22	17.20	12.75
9	86.58	15.20	14.32	16.94	12.84
10	88.42	15.60	14.46	17.05	13.02
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.23	0.44	0.03	18.75	

II: Corporate bond

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	38.92	17.88	20.26	2.39	13.39
2	54.85	34.16	22.38	5.33	15.91
3	67.14	36.70	31.35	19.82	24.53
4	76.07	38.64	36.87	24.78	30.91
5	80.93	40.93	37.50	24.83	31.46
6	84.57	41.86	38.12	24.26	32.10
7	87.83	42.96	38.82	25.13	32.68
8	89.75	43.45	39.29	25.09	33.12
9	91.35	43.86	39.72	24.80	33.69
10	92.56	44.21	40.06	26.57	34.21
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	1.99	-0.22	1.22	48.57	

III: Option

K	R^2_K	R^2	$R^2_{f,O}$	$R^2_{f,T,N,O}$	$R^2_{f,N,T,O}$
1	37.94	11.79	2.35	15.79	4.80
2	54.87	13.74	2.54	15.42	5.14
3	65.45	17.68	2.83	9.81	5.14
4	76.10	19.36	3.16	15.30	5.93
5	81.92	20.49	3.37	15.22	6.30
6	85.41	21.00	3.47	14.08	6.45
7	88.24	21.95	4.02	13.80	6.96
8	90.74	22.32	4.15	14.26	7.15
9	92.29	22.95	4.44	15.43	7.43
10	93.64	23.30	4.54	17.45	7.62
K	R^2_O	$R^2_{T,N,O}$	$R^2_{N,T,O}$	$R^2_{\tilde{R}}$	
1-10	0.17	0.85	0.57	27.28	

[†]K: the number of factors specified; $R^2_{\tilde{R}}$: Fama-MacBeth cross-sectional regression R^2 (%); R^2_K: the variation of the Fama-MacBeth managed portfolios $\tilde{R}_t$ captured by the common factors; R^2: total in-sample R^2 (%), defined in (5.1); $R^2_{f,O}$, $R^2_{f,T,N,O}$, $R^2_{f,N,T,O}$ (R^2_O, $R^2_{T,N,O}$, $R^2_{N,T,O}$): various out-of-sample fit (predictive) R^2 (%), defined in (5.4).

Table B18: Out-of-sample Sharpe ratios of joint and asset-class-specific MVE portfolios[†]

Number of factors	Joint	Stock	CorpBond	Option
$K = 1$	1.47	-0.12	0.60	1.36
	-	[1.97]	[0.68]	[1.48]
$K = 2$	1.68	0.10	0.80	1.40
	-	[1.90]	[0.64]	[1.59]
$K = 3$	1.96	0.30	0.29	1.85
	-	[2.18]	[0.78]	[1.88]
$K = 4$	2.46	0.99	-0.44	2.02
	-	[2.25]	[0.87]	[1.83]
$K = 5$	2.41	1.05	-0.56	2.00
	-	[2.78]	[0.83]	[2.01]
$K = 6$	2.30	1.30	-0.83	1.98
	-	[2.73]	[0.86]	[2.08]
$K = 7$	2.43	2.00	-1.11	2.13
	-	[2.31]	[0.74]	[1.67]
$K = 8$	2.46	2.10	-1.15	2.13
	-	[2.33]	[0.75]	[1.66]
$K = 9$	3.07	1.72	0.02	2.21
	-	[2.51]	[0.71]	[1.90]
$K = 10$	3.06	1.87	0.11	2.25
	-	[2.40]	[0.77]	[1.92]
$K = 11$	3.11	2.23	0.25	2.20
	-	[2.41]	[0.80]	[1.89]
$K = 12$	3.15	2.24	0.07	2.26
	-	[2.52]	[0.74]	[2.22]
$K = 13$	3.31	2.24	0.71	2.26
	-	[2.56]	[0.77]	[2.09]
$K = 14$	3.40	2.19	1.00	2.28
	-	[2.56]	[0.82]	[1.81]
$K = 15$	3.40	2.15	1.46	2.21
	-	[2.50]	[0.63]	[1.82]
$K = 16$	3.42	2.16	1.35	2.17
	-	[2.56]	[0.59]	[1.92]
$K = 17$	3.48	2.08	1.25	2.25
	-	[2.78]	[0.64]	[2.26]
$K = 18$	3.51	2.09	1.26	2.24
	-	[3.05]	[0.65]	[2.23]
$K = 19$	3.70	2.17	1.27	2.34
	-	[3.11]	[0.72]	[2.35]
$K = 20$	3.62	2.11	1.25	2.27
	-	[3.19]	[0.74]	[2.65]

[†] 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.

Figure B6: Estimates of coefficients B for the second to fourth common factor with 95% confidence intervals

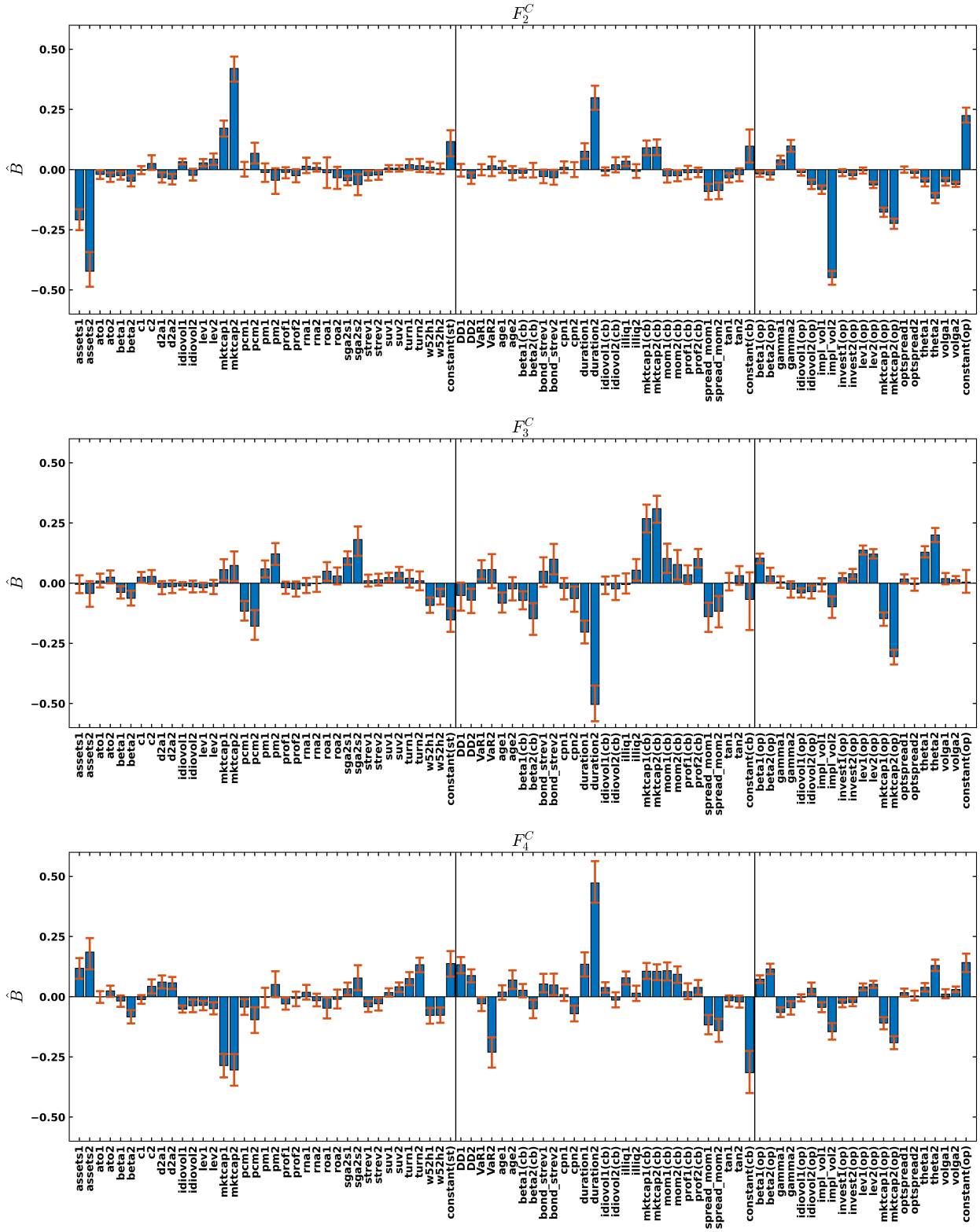


Figure B7: Estimates of coefficients B for the fifth to seventh common factor with 95% confidence intervals

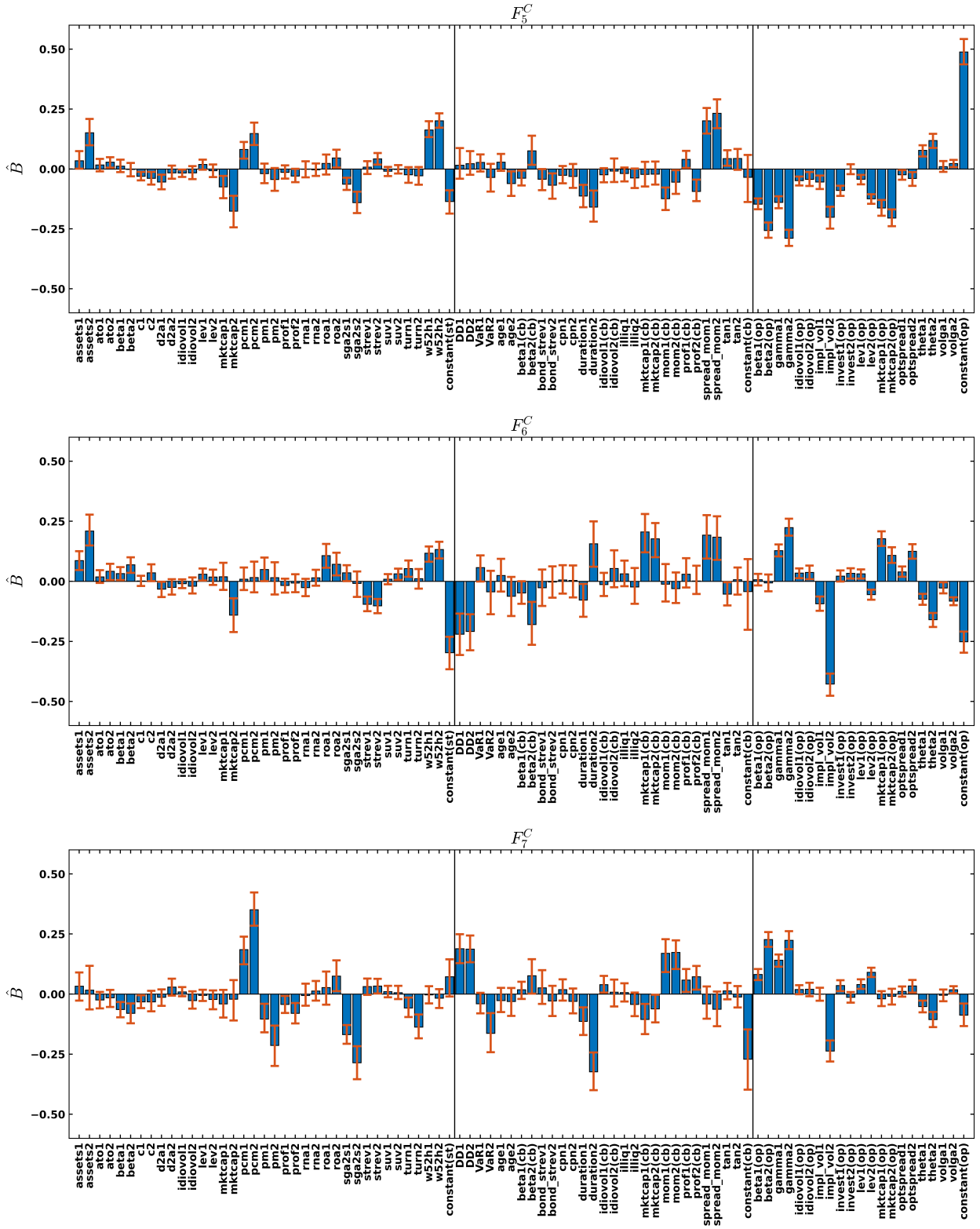
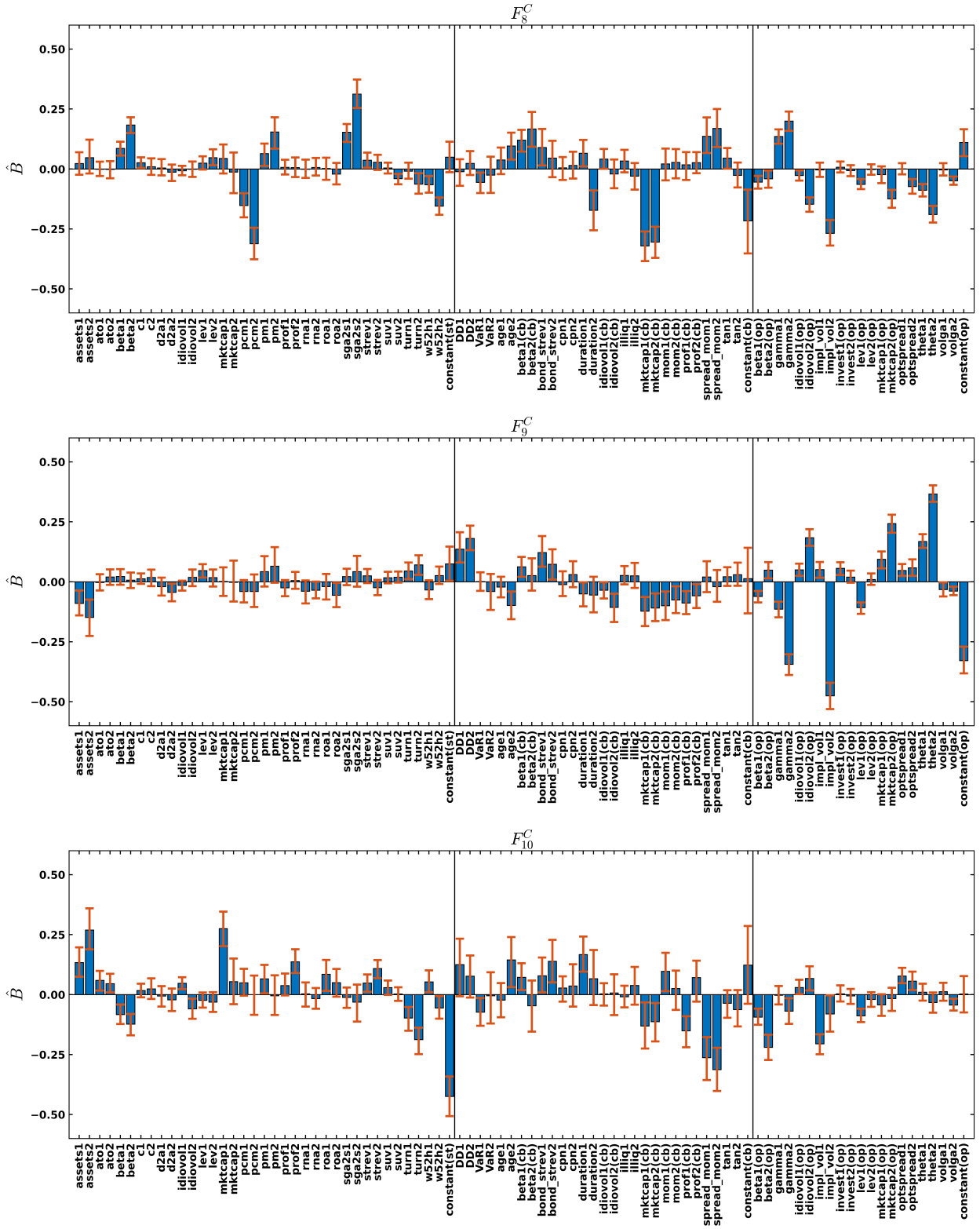


Figure B8: Estimates of coefficients B for the eighth to tenth common factor with 95% confidence intervals



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