Pervasive Styles *

Huaixin Wang Jianfeng Yu

August 2026

Abstract

The performance of investment styles positively predicts stock returns because of positive feedback trading. This paper examines the heterogeneity and dimensionality of style pricing effects. Employing a comprehensive set of 312 firm characteristics, we show that over 84% of style-based trading strategies yield significantly positive returns. The style pricing effect is stronger under several conditions: (1) heightened return comovement; (2) intensified institutional style trading; (3) more retail participation; (4) greater style attractiveness; and (5) lower implementation complexity. Placebo tests using over 42,000 accounting ratios and randomly generated styles show that the pricing effect arises primarily from characteristics relevant to investment practice rather than from arbitrary ones. Identifying styles in high-dimensional spaces enhances strategy performance, while a sparse model based on principal components of characteristics captures much of the return predictability.

JEL Classification: G11, G12, G23, C55

Keywords: Style investing, Predictability, Asset management, Big data

*We thank Jingda Yan and seminar participants at the University of Macau FBA for helpful comments. All errors are our own. Author affiliation/contact information: Huaixin Wang is with the Faculty of Business Administration, University of Macau (huaixinwang@um.edu.mo); Jianfeng Yu is with the School of Economics and Management, Tsinghua University (yujf@sem.tsinghua.edu.cn).

1 Introduction

Investors routinely classify stocks into styles (e.g., value versus growth) and allocate capital across categories. Retail investors exhibit habitat preferences due to categorical thinking (Peng and Xiong, 2006; Green and Hwang, 2009) or personal experience (Huang, 2019), while institutions adopt style-based mandates to specialize strategies and cater to market attention (Froot and Teo, 2008; Ben-David et al., 2023).[1] Coordinated demand at the category level induces return comovement beyond what fundamentals justify, and the price pressure from chasing style performance generates predictability in asset returns (Lewellen, 2002; Mullainathan, 2002; Barberis and Shleifer, 2003).[2] Episodes such as the internet bubble (Brunnermeier and Nagel, 2004; Griffin et al., 2011) and the quant meltdown (Khandani and Lo, 2011) illustrate that style-induced price pressures can emerge rapidly, propagate broadly, and materially affect both individual stocks and market stability.

The existing evidence, however, is largely confined to a handful of prominent indices, such as value and momentum, raising important unanswered questions. First, investment strategies adopted in practice are remarkably diverse (Buffa and Hodor, 2023; Pavlova and Sikorskaya, 2023). As such, the pool of candidate styles with potential market impact is broad, raising concerns about selection and publication bias. Second, assets grouped into the same style category tend to share correlated fundamentals. Focusing on a single characteristic thus makes it difficult to distinguish the price pressure channel from alternatives such as investor underreaction (Cohen and Frazzini, 2008). Moreover, recent studies (Kozak et al., 2020; Giannone et al., 2021; Didisheim et al., 2023; Chen and McCoy, 2024) point to the high-dimensional nature of stock return predictability and the economic gains from incorporating additional features. Therefore, an empirical examination of style-driven price impacts, using a wide array of firm characteristics, is both pertinent and desirable.

This paper makes three key points. First, we show that return predictability arising from style investing is *pervasive* across a comprehensive set of characteristics. Notably, this style effect emerges even when the underlying characteristic itself lacks predictive power. Second, and more importantly, we investigate what drives the strength of the variation in the

[1] A survey of investors managing $22.3 trillion in assets (Invesco, 2024) documents growing reliance on systematic style and factor strategies, with 91% adjusting their factor allocations over time.

[2] Empirical studies corroborate these insights, documenting that stocks within the same category covary excessively (Barberis et al., 2005; Green and Hwang, 2009; Boyer, 2011; Hameed and Xie, 2019) and that investment styles influence cross-sectional stock returns (Chen and De Bondt, 2004; Wahal and Yavuz, 2013; Chou et al., 2019; Ben-David et al., 2022, 2024).

style effect. While return predictability is widespread, there exists substantial *heterogeneity* consistent with the price pressure hypothesis. Third, we assess the extent to which these styles can be captured in a parsimonious model, given style-induced trading as their *common* driver. High dimensionality is required to capture the documented return predictability; sparsity becomes achievable when using principal components of characteristics for style classification. These cross-style examinations enable us to assess the market impact of style investing in a manner that is difficult to approach using only a single characteristic.

Specifically, we expand the set of candidate style dimensions by incorporating 312 firm characteristics that have been studied in the empirical asset pricing literature (Chen and Zimmermann, 2022). For *each* characteristic, we construct stock-level style signals by grouping stocks into size-characteristic sorted portfolios and computing average returns of peer stocks in the same style category. We then sort stocks on these style signals and form long-short strategies that buy stocks within the top decile and sell those within the bottom decile. If investors chase style performance and engage in positive feedback trading, then the corresponding long-short strategy should yield positive profits. Among the 312 styles examined, we find that 289 trading strategies, using value-weighted portfolios, generate positive returns that are significant at the 5% level. Depending on factor adjustments, between 263 and 290 strategies remain significant. This finding indicates that a minimum of 84% of the style signals demonstrate predictive ability for stock returns.[3]

A well-documented phenomenon in asset pricing is the tendency for anomalies to attenuate over extended sample periods. In our sample, only 118 characteristic-based trading strategies earn significant returns. In contrast, the majority of style signals deliver significant predictive power for returns, and their performance appears largely unrelated to the profitability of characteristic strategies. When partitioning characteristics by their own predictive ability, the style strategies derived from all groups consistently generate significant returns regardless of whether the underlying characteristic itself exhibits predictive power.

As a placebo test, we conduct an exhaustive search over more than 42,000 pairwise Compustat accounting ratios. Only about 16% yield significant style effects, and these cluster around economically salient categories such as earnings, assets, and market price. A complementary test using randomly generated styles confirms that the pervasive return

[3]To clarify, the term "predictability" in this paper specifically refers to cross-sectional *individual stock* returns, which is related to but different from portfolio-level characteristic momentum (Lewellen, 2002; Arnott et al., 2023) or time-series factor momentum (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022). Unlike these studies, this paper dissects predictability by focusing on the *heterogeneity* across a large set of styles rather than proposing a composite momentum trading strategy. Section 3.8 provides further discussion.

predictability disappears when economic content is absent.

Having established the prevalence of style-based pricing effects, we turn to investigating their key determinants. In theoretical work, Barberis and Shleifer (2003) propose that style investing creates return comovement because of coordinated demand, and the pursuit of style-level performance leads to return predictability. The large set of characteristics enables us to test several predictions of this mechanism by analyzing cross-style heterogeneity. In our first test, we hypothesize that higher return comovement implies a higher degree of synchronized trading, therefore generating stronger predictability. Consistently, we find that styles associated with greater comovement exhibit higher strategy returns. Style-level panel regressions show that an increase in lagged comovement by one standard deviation is associated with an increase in subsequent strategy returns by 10.4 (8.0) basis points in the cross section (time series).

Different characteristics (styles), in practice, exhibit varying degrees of importance in the designation of style investing. Therefore, the pricing effect of a style should be more evident when it is widely adopted in trading strategies. This motivates our test on the role of investors' trading behavior. In particular, institutional investors play a dominant role in style investing and positive feedback trading (Froot and Teo, 2008; Choi and Sias, 2009; Wahal and Yavuz, 2013; Frijns et al., 2016; DeVault et al., 2019). If shifts in institutional demand align with style signals, that would indicate a higher likelihood of style chasing and, consequently, stronger price impacts.

We measure the propensity of institutional style trading (PIST) on styles by regressing changes in institutional ownership on style signals. The results show that a one standard deviation increase in PIST corresponds to an approximate 4.9 bps increase in future style strategy returns, both in the cross section and time series. This positive relationship also distinguishes style investing from an underreaction-based explanation. If the return predictability from style grouping reflects the slow dissemination of connected fundamental news (Cohen and Frazzini, 2008), then increased PIST should alleviate mispricing by facilitating the incorporation of information. However, our findings reveal that institutional style trading is associated with amplified anomaly returns. We also estimate an analogous measure for retail investors' trading and find that a heightened tendency for retail investors to chase style trends corresponds to stronger style pricing effects.

Style investing also posits that investors categorize stocks based on characteristics without speculating on their long-term profitability. Transient fluctuations in relative returns across

categories motivate style-chasing behavior. For example, when value stocks substantially outperform growth stocks, investors are drawn to the value style and increase their allocation accordingly. The reverse holds as well: investors chase the trend of growth stocks if they outperformed value stocks. In either scenario, the style strategy based on the value characteristic (i.e., book-to-market ratio) tends to yield higher returns. Consistently, we show that characteristic return spreads in absolute terms predict stronger future style returns.

The last aspect we examine is the complexity of characteristics. Implementation hurdles significantly influence the adoption of characteristics in style investing and hence their subsequent impact on the stock market. Using a large language model, we evaluate the complexity of 312 characteristics based on their detailed textual descriptions. Characteristics with lower complexity are associated with stronger style-pricing effects. This finding supports the hypothesis that characteristics that are conceptually clear, computationally simple, and readily accessible are more likely to be adopted in style investing.[4]

A growing literature on factor momentum documents that characteristic-based factors exhibit a positive short-run autocorrelation (Ehsani and Linnainmaa, 2022; Arnott et al., 2023), implying that a factor's recent outperformance tends to persist into the next period. Thus, firms in the smallest size decile are likely to outperform firms in the largest size decile when they have done so over the prior year, a finding similar in spirit to our style strategies at first glance. However, style strategies differ substantially from factor momentum in that the former compares peer performance across characteristic-sorted portfolios, whereas factor momentum focuses on the extreme (long and short) portfolios. We show that our style portfolio strategies only involve less than 23% of the stocks in the extreme decile portfolios, distinct from the traditional factor momentum analysis which only uses stocks with extreme characteristics. Thus, the predictive ability of style signals should not be attributed solely to momentum in the long- or short-leg characteristic portfolios. In addition, we find that more than half (53%) of the 312 styles continue to generate significantly positive returns after controlling for factor momentum, indicating that factor momentum alone cannot fully account for our results. Most importantly, we investigate how our documented patterns in style effects can be used to understand the economic force underlying the autocorrelation in factor returns. We find support that style-induced positive feedback trading could be one of

[4]Furthermore, the negative correlation between characteristic complexity and the style effect suggests that investor underreaction is unlikely to be the primary driver of our findings. This is because the underreaction hypothesis would imply that highly complex characteristics, being more difficult to perceive and compute, should lead to stronger underreaction and predictability. However, our empirical results indicate the opposite pattern.

the important channels for the observed factor momentum.

As we document the pervasiveness of style-induced return predictability across a broad range of characteristics, a natural question arises regarding the dimensionality required to capture this effect (Cochrane, 2011). To this end, we examine the correlation structure of styles. The pair wise correlations between style strategy returns cluster around 0.60, with the first principal component (PC) explaining around 58% of the total variation. This result contrasts sharply with the structure of characteristics, where pairwise correlations are generally close to zero (Green et al., 2013; McLean and Pontiff, 2016; Yan and Zheng, 2017; Chen and Zimmermann, 2022; Chen and McCoy, 2024).

To further investigate the role of dimensionality in style-induced return predictability, we employ k-means clustering, a standard machine learning algorithm, to construct styles in a high-dimensional setting. This approach assigns stocks to groups within a d-dimensional style space, after which we calculate style signals and form long-short portfolios analogously. By examining style strategy performance under different d values, we find that a *high* dimension is required to capture the return predictability stemming from style investing. In particular, the strategy return and Sharpe ratio tend to increase in d, and more than 200 characteristics are required to reach the potential 30% annualized returns (value weighted) and 1.20 annualized Sharpe ratios. While style signals in high-dimensional spaces are constructed without explicitly estimating forecast models, the results indicate that incorporating more characteristics provides economic improvements in explaining expected returns. This finding complements and extends previous evidence on characteristics-based models (Kozak et al., 2020; Bessembinder et al., 2021; Chen and McCoy, 2024).

Interestingly, sparsity emerges when style groups are identified based on the principal components of characteristics. Upon transforming characteristics into PCs, we find that styles constructed using a few high-eigenvalue PCs capture nearly all the returns delivered from high-dimensional characteristic models. This finding echoes Kozak et al. (2020), who find that sparse PC-based models perform well in describing cross-sectional returns. The dimensionality-sparsity pattern is intuitive. On the one hand, individual characteristics capture different facets of style investing practice, which is inherently complex. Increasing dimensionality therefore adds incremental information. On the other hand, each characteristic is a *noisy* proxy. PCs yield a cleaner representation of the latent cluster structure and the underlying common demand shocks and thus do a better job of capturing the price pressure. Taken together, these findings highlight the pervasive adoption of style investing and its systematic influence on financial markets.

A series of additional tests validate the robustness of our main findings. First, the return predictability might be contaminated by the short-term reversal effect (Lehmann, 1990; Lo and MacKinlay, 1990) since stocks within the same style group tend to have positively correlated returns. Consistently, style signals orthogonal to focal stocks' contemporaneous returns indeed exhibit stronger predictive ability. Second, we impose stricter liquidity requirements on the sample and consider alternative portfolio specifications. The return predictability from style clustering remains pervasive. Third, the return predictability persists when considering styles both within and across industries, suggesting the predictive ability of characteristics-derived style signals is not driven entirely by industry-level positive feedback trading. Lastly, we examine style signals from alternative constructions and datasets, yielding similar results.

Related literature. A large body of work provides empirical examinations of the seminal study by Lewellen (2002) and Barberis and Shleifer (2003). In particular, the literature documents evidence on style-level asset allocation (Teo and Woo, 2004; Froot and Teo, 2008; Choi and Sias, 2009; Kumar, 2009; Wermers, 2012; Schauten et al., 2015; Frijns et al., 2016; Broman, 2022), within-style comovement (Barberis et al., 2005; Greenwood, 2008; Green and Hwang, 2009; Boyer, 2011; Hameed and Xie, 2019), and return predictability (Chen and De Bondt, 2004; Wahal and Yavuz, 2013; Jame and Tong, 2014; Chou et al., 2019; Ben-David et al., 2022, 2024). This paper broadens the universe of candidate styles and shows that the influence of style investing might be more extensive and profound than previously documented. The heterogeneity analyses provide further evidence on how diverse trading strategies generate systematic price impacts. Therefore, the findings also have practical implications such as managing crowding risk.

A prominent feature of the empirical asset pricing literature is the emergence of meta-studies (Hou et al., 2020; Chen and Zimmermann, 2022; Jensen et al., 2023) and large-scale examinations of stock return anomalies (McLean and Pontiff, 2016; Green et al., 2017; Chen et al., 2022a; Bowles et al., 2024; Muravyev et al., 2025). This paper introduces a new stylized fact: returns are generally predictable through categorizing stocks into styles, even if the underlying characteristic lacks predictive ability.[5] Recent studies demonstrate the persuasiveness of high dimensionality and complexity over sparsity and parsimony in

[5]Nonetheless, caution is advised when interpreting these findings, as our intention is not to propose a "zoo" of styles (Cochrane, 2011). Indeed, not every characteristic holds primary importance in designating real-world investment strategies. It is possible that certain styles are subsidiaries of several dominant dimensions. Instead, the pervasive predictability of returns suggests a widespread influence of style-based investing on equity pricing.

describing expected returns (Kozak et al., 2020; Giannone et al., 2021; Bessembinder et al., 2021; Didisheim et al., 2023; Kelly et al., 2024). Aligning with this perspective, our findings point to identifying styles in a high-dimensional space to capture the pricing implications of the diverse, complex investment strategies used in practice. A sparse representation of style clusters becomes feasible when working in the PC space, which complements the insights of Kozak et al. (2020).

An expanding body of research employs machine learning methods to combine multiple predictors into return forecasts (Gu et al., 2020; Cong et al., 2020; Chen et al., 2024; Bryzgalova et al., 2025). Our findings suggest that large economic gains are achievable even when the model is not explicitly trained to predict returns. The enhanced predictability arises from a more refined representation of the underlying stock cluster structure, which captures coordinated style demand-induced price pressure. Recent work explores media narratives and their market implications (Goetzmann et al., 2022; Bybee et al., 2023, 2024; Lee et al., 2024; Hirshleifer et al., 2025a,b). These methodological advances offer promising avenues for extending style portfolio construction.

The rest of the paper is organized as follows. Section 2 describes data and variable constructions and reports the performance of style strategies. Section 3 investigates the determinants and sources of style effects. Section 4 explores the dimension of style effects. Section 5 presents additional robustness tests. Section 6 concludes.

2 Styles and Return Predictability

Our sample includes all common stocks (share codes 10 or 11) listed on NYSE, AMEX, and NASDAQ between June 1963 and December 2021. We obtain stock price data from CRSP and accounting data from Compustat. We restrict the sample to non-financial firms and require a share price of at least $1 at the portfolio formation date. Additionally, a stock must have at least 10 available trading days in the previous month to be included in trading strategies. Monthly time series of asset pricing factors (Fama and French, 1996, 2015) are downloaded from Kenneth French's Data Library.

2.1 Characteristics data and construction of style signals

The firm-level characteristics data are downloaded from the Open Source Asset Pricing (OSAP) dataset by Chen and Zimmermann (2022). This dataset provides comprehensive coverage of the characteristics studied in Harvey et al. (2016), McLean and Pontiff (2016), Green et al. (2017), and Hou et al. (2020), thereby offering an expansive repository of information related to stock returns.[6] We begin with 204 "predictors" (i.e., characteristics that have been shown to significantly predict future returns in their original papers) and 113 "placebos" (i.e., characteristics that do not exhibit clear predictive ability).[7] To effectively utilize the data while maintaining a reasonable sample size, we require at least 50 available stocks each month and exclude characteristics with less than five years of available data or with a sample period ending in the early 2000s. This process leaves us with 312 firm characteristics in total.[8]

Figure 1 illustrates the timeline for constructing style signals and testing return predictability. At the end of each June, we categorize stocks into 5×5 portfolios based on market capitalization and one specific characteristic. NYSE breakpoints are used for the size dimension. For characteristics with discrete values, we assign stocks into $5\times N$ groups based on size and the characteristic if the number of categories (N) is less than 5. Otherwise, we continue to use the 5×5 assignment.[9] The resulting style assignments remain fixed throughout the following 12 months until the next June, when new style clusters are

[6]For more details on the dataset, please refer to `https://www.openassetpricing.com/`. We are grateful to Andrew Chen and Tom Zimmermann for making the data available.

[7]Specifically, placebos are characteristics that Chen and Zimmermann (2022) classify as either "Not-Predictor" or "Indirect Signal." These include: (1) characteristics for which the original studies report weak or statistically insignificant predictive ability and (2) alternative constructions or modified versions of previously proposed characteristics (Hou et al., 2020). Such variables either lack robust evidence of predictive power or are expected to be statistically insignificant in long-short portfolios.

[8]The excluded characteristics are the institutional ownership among high short interest (Asquith et al., 2005), the takeover vulnerability (Cremers and Nair, 2005), active shareholders (Cremers and Nair, 2005), the governance index (Gompers et al., 2003), and the probability of informed trading (Easley et al., 2002). The corresponding variables in the Chen and Zimmermann (2022) database are *IO_ShortInterest*, *Activism1*, *Activism2*, *Governance*, and *ProbInformedTrading*, respectively. In addition, the set of 312 candidate characteristics does not encompass price, size, or monthly stock return, as these variables are omitted from the OSAP database.

[9]We use two-way categorization by combining size and characteristics when constructing styles, given the fundamental importance of market capitalization in real-world investment practices. For example, size serves as a strong proxy for liquidity, information quality, transaction costs, and prominence in the product market. Additionally, size also stands as one of the main building blocks of modern asset pricing models, as every characteristic-based factor involves a size-neutral setup. Nevertheless, in the robustness section, we find that the predictive ability of style signals remains prevalent even when style groups are identified without the size dimension.

identified. Each month, for each stock, we compute a style signal for a given characteristic. This signal is the value-weighted average return of other stocks belonging to the same style group. We then form decile portfolios based on the constructed signal and examine the realized returns during the subsequent month.[10]

2.2 Performance of style-based strategies

We calculate both raw excess returns and factor-adjusted returns for each long-short style strategy. Benchmark models include CAPM, the three-factor model (FF3) of Fama and French (1996), the four-factor model (Carhart) of Carhart (1997), the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6). While we report both value-weighted and equal-weighted results, our main analysis relies on value-weighted portfolios.

Figure 2 presents the count of strategies exhibiting significant returns and those without. We find that the majority of style signals display significant predictive ability for future stock returns. Out of 312 characteristics examined, 289 of the associated style-based trading strategies yield returns with t-statistics exceeding 1.96 under value weighting. The number of significant strategies decreases to 273 under the five-factor model and further falls to 263 under the six-factor model. In general, over 84% (263/312) of style signals positively and significantly predict future stock returns. Furthermore, nearly all style-based strategies earn significant returns under equal weighting. These results suggest the pervasive return predictability stemming from style categorization.[11]

Figure 3 plots the distributions of five-factor (Fama and French, 2015) alphas and the corresponding t-statistics of the 312 style-based strategies. It shows that the factor-adjusted returns center around 0.60% and a substantial fraction of strategies are significant at the 1% level. The first two panels of Table 1 report the summary statistics of style strategies having a t-statistic of at least 1.96 in more detail. Panel A shows that, on average, the monthly return to the style-based long-short portfolios is 0.70%, and the overall performance ranges from 0.30% to 1.21%, depending on style and factor model specifications. Panel B reports the

[10]In the robustness section, we also explore alternative portfolio specifications and constructions of style signals and utilize additional data sources of firm characteristics. The main findings of this study remain robust across these variations.

[11]Notably, style strategies either yield positive returns or yield returns that are negative but statistically indistinguishable from zero. Significantly negative returns are absent in the constructed strategies. Appendix Figure A1 shows that the pervasive return predictability remains robust across a range of alternative portfolio specifications.

t-statistics of style-based strategies. It shows that over 77% of them earn a factor-adjusted return that is significant at the 1% level ($t \geq 2.58$). In terms of excess returns, 76% of the strategy t-statistics exceed the threshold of 3 (Harvey et al., 2016).

Figure 4 shows the return distribution of style strategies by benchmark models, with outstanding styles marked.[12] Consistent with previous studies, the value style (based on book-to-market) emerges as one of the strongest predictors. More importantly, BM is not the only standout style, as the result reveals alternative characteristics delivering a comparable predictive ability. For example, style strategies based on the sales-to-price ratio (SP) and the R&D-to-sales ratio (rd_sale) also exhibit strong profitability, with monthly alphas exceeding 1%. These findings indicate that a comprehensive consideration of various firm characteristics beyond BM enriches the evidence on style-induced price impacts.

2.3 Relation with characteristic-based strategies

A natural question arising from our findings is whether the performance of style portfolios depends on the predictive ability of the underlying characteristics. Figure 5 illustrates the relation between the performance of style-based strategies (SS) and characteristic-based strategies (CS). We consider both the ex post (left panel) and ex ante (right panel) performance of CS. Specifically, in the left panel, we construct value-weighted portfolios for each of the 312 firm characteristics and compute long-short strategy returns from July 1963 to December 2021. Since many characteristics do not exhibit clear predictive ability, we consider the average CS returns in absolute value. In the right panel, we use the CS returns reported in the original papers' tests, which are provided by Chen and Zimmermann (2022) and restricted to a subset of characteristics. In both cases, Figure 5 shows that the return of SS exhibits only a marginal relationship with the performance of CS, as evident by the close-to-zero slopes.

In Table 2, we further partition characteristics into two groups based on whether they display significant predictive power in the extended sample (Panel A) or in the original sample (Panel B). The table summarizes the conditional performance of SS. It shows that the strength of the style-pricing effect is nearly equivalent across these two groups. Within the subset of characteristics with $|t_{CS}| \geq 1.96$, Panel A shows that a notable 97% of the

[12] We use the characteristic acronym as in Chen and Zimmermann (2022) in presenting style variables. A detailed description can be found in the *Signal Documentation* at `https://www.openassetpricing.com/data/`.

corresponding SS generate returns that are significant at the 5% level. For the remaining characteristics, 88% of the derived style signals still display significant predictive ability. Similar patterns are observed in Panel B, where we use the t-statistics reported in the original studies to partition characteristics.[13] The majority of style signals exhibit strong predictive power, regardless of the factor model used; in contrast, most CS fail to earn significant profits in the extended sample. As such, these results indicate that style signals differ from the conventional characteristic-based model in its capacity to explain cross-sectional stock returns.

This finding is broadly intuitive. Consider a characteristic with strong historical predictive power, such as book-to-market. As both arbitrageurs and style investors direct attention to this characteristic, arbitrage weakens the characteristic-based anomaly over time, whereas style-driven demand persists and sustains the style-based strategy. The next section examines what drives the cross-sectional variation in style effects.

3 Determinants and Sources of Style Effects

This section delves into the factors influencing the performance of style strategies. First, we examine the relationship between return comovement and return predictability across styles. Next, we investigate how the returns of style strategies vary with institutions' style trading. Third, we study the role of retail participation. Fourth, we show that characteristic attractiveness serves as a powerful predictor of strategy performance. Fifth, we leverage large language models to examine how the complexity of a characteristic relates to the style effect. Placebo tests based on arbitrary accounting ratios and purely random characteristics provide further evidence. Lastly, we discuss the mechanism at play and alternative channels.

3.1 Comovement and profits of style strategies

The premise underlying the return predictability we study is style-level capital allocation. As in the model of Barberis and Shleifer (2003), the demand for a stock is expressed at the level of style categories, and coordinated demand leads to excess comovement. Specifically, higher comovement implies a higher degree of synchronized investing at the style level and therefore should indicate a stronger predictive ability of the style signal.

[13]The data on in-sample t-statistics are provided by Chen and Zimmermann (2022).

We calculate style wise comovement by computing the contemporaneous correlation coefficient between the focal stock's monthly return and the style signal. Take the book-to-market ratio as an example. Each month t, we define $Comove_{BM,t}$ as the cross-sectional correlation, $Corr[R_{i,t}, R_{BM(i),t}]$, where $R_{i,t}$ is the focal stock's monthly return and $R_{BM(i),t}$ is the value-weighted average return of other stocks within the same size-BM group. If there are N stocks in month t, this computation uses $\{R_{i,t}\}_{i=1}^{N}$ and $\{R_{BM(i),t}\}_{i=1}^{N}$ as inputs and produces a single correlation value, $Comove_{BM,t}$. We conduct this calculation each month for each style, which generates a panel of comovement measures.

Then, we estimate the following panel regression to examine the relationship between comovement and the style effect:

$$R_{style,t+1} = \alpha + \beta Comove_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}, \tag{1}$$

where the dependent variable $R_{style,t+1}$ is the realized return of the style strategy, and the main independent variable of interest, $Comove_{style,t}$, is the lagged comovement. We include time-fixed effects η_t and style-fixed effects γ_{style} in the regressions.

Table 3 reports the results. In column (1), we include time-fixed effects and examine the cross-sectional variation in style strategy returns. Consistent with our hypothesis, we find that styles with higher comovement tend to earn higher returns in the future. A one standard deviation increase in lagged comovement is associated with an increase in subsequent strategy returns of 10.4 bps in the cross section. In column (2), we include style fixed effects solely to study the time-series variation in comovement and strategy profits. The estimated slope is positive and significant, with a t-statistic of 2.78. Economically, the coefficient suggests that a one standard deviation increase in comovement implies an increase in future returns of 8 bps. In columns (4) to (6), we use two-way clusters and re-estimate the t-statistics. The results are not sensitive to these specifications, and the estimated coefficient on $Comove_{style,t}$ is quantitatively similar.[14]

[14]We note that the positive comovement-return relationship is also consistent with a risk-based interpretation. If firms within the same style group share exposure to common fundamental risks, then higher comovement may reflect greater correlated fundamental risk and, therefore, higher expected returns as compensation. We discuss potential mechanisms in more detail in Section 3.8.

3.2 Institutional trading and enhanced style pricing effects

A more direct way to gauge the degree of style investing is to examine how investors respond to style signals. Intuitively, a style should be associated with stronger return predictability if it receives more attention. To proxy for investor demand, we obtain firm-level institutional ownership data from the Thomson Reuters Institutional Managers (13F) Holdings database. The main reason we focus on institutional investors, besides data availability, is that the dominant role makes them more likely to generate market-wide price impact from style investment (Froot and Teo, 2008; Choi and Sias, 2009; Wermers, 2012; Frijns et al., 2016; Wahal and Yavuz, 2013).

For each style signal, we define the propensity of institutional style trading (PIST) through quarterly cross-sectional regressions:

$$\Delta Inst_{i,q} = a_q + PIST_{style,q} R_{i,q}^{style} + b_q X_{i,q} + \varepsilon_{i,q}, \tag{2}$$

in which the dependent variable, $\Delta Inst_{i,q}$, is the quarterly change in stock i's institutional ownership.[15] The main independent variable $R_{i,q}^{style}$ is the cumulative style return of stock i over quarter q. The estimated coefficient, $PIST_{style,q}$, captures the extent to which institutional investors' trading aligns with the style signal. Specifically, a positive and larger $PIST_{style,q}$ implies a higher propensity of institutional investors to engage in style investing. In each regression, $X_{i,q}$ is the vector of control variables, including stock i's quarterly return, the cumulative one-year return as of the last quarter, firm size, the book-to-market ratio, idiosyncratic volatility, gross profitability, and the investment-to-assets ratio.[16] Independent variables are lagged for one month relative to $\Delta Inst_{i,q}$.

Figure 6 presents the distribution of the estimated PIST. We calculate the average and median values of time series $\{PIST_{style,q}\}$ and then report the distributions of PIST for the 312 style signals. Consistent with the conjecture that institutions tend to trade at the style level, we find that the average PIST is positive for most signals. The median PIST again confirms that institutional investors are inclined to trade the focal stock in the same direction as the style signal varies. Take the quarterly book-to-market ratio (BMq) as an

[15] Institutional ownership ($Inst$) is the shares held by institutional investors (as reported in 13F filings) divided by the total shares outstanding. Following Nagel (2005), $Inst$ below 0.0001 and above 0.9999 are replaced with 0.0001 and 0.9999, respectively.

[16] In each estimation, independent variables are winsorized at the 1% and 99% levels and then standardized to have zero mean and unit variance. Therefore, $PIST$ quantifies the change in institutional ownership in response to a one standard deviation increase in the style signal.

example. The average PIST of BMq is 0.10%, while the average standard deviation of $R_{i,q}^{BMq}$ is 6.67%. This implies that an increase in the BMq style signal of 1% is associated with an increase in institutional ownership of 0.015% (0.10/6.67).

We adopt a similar regression-based method to examine the effect of institutional trading on style returns:

$$R_{style,t+1} = \alpha + \beta_1 PIST_{style,t} + \beta_2 Comove_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}, \tag{3}$$

where the independent variable $PIST_{style,t}$ is the estimated propensity of institutional style trading in the most recent quarter. Table 4 reports the regression results. We find that PIST positively predicts future style strategy returns. Columns (1) to (3) of Panel A show that a one standard deviation increase in lagged PIST is associated with an increase in the subsequent style return of around 4.9 to 5.0 bps. In columns (4) to (6), we further control for lagged comovement. It shows that the estimated coefficient on PIST remains nearly unchanged, with a t-statistic around 2.25 to 2.36.

The positive relationship between PIST and future style returns provides new evidence that institutional investors exacerbate mispricing (Edelen et al., 2016; Agarwal et al., 2022). It also runs counter to an underreaction explanation of predictability. Specifically, since firms within the same style group share similar fundamentals, the documented return predictability is potentially driven by slow information dissemination among economically connected firms (e.g., Cohen and Frazzini (2008)). If investor underreaction is the primary driving force, then PIST should exhibit a *negative* relationship with future style returns. This is because such a channel would imply that value-relevant information is incorporated more efficiently when PIST increases, thus mitigating mispricing.[17] However, we find that PIST has a strongly positive predictive ability for style strategy returns. Therefore, the findings align more closely with the hypothesis that the return predictability stems from style-level investing of institutions, rather than being attributed to underreaction arising from economic linkages.[18]

[17]Indeed, Cohen and Frazzini (2008) find a substantial reduction in the lead-lag effect when there is a higher level of mutual fund common ownership.

[18]It is important to note that this conclusion is drawn from an average perspective. There is certainly a possibility that for some characteristics, the predictability is linked to fundamental news rather than style-driven investment. In a later analysis, we provide another test to further distinguish between style investing and underreaction based on complexities of characteristics.

3.3 Retail trading and style strategy performance

While institutional investors play an important role in style investing, previous studies find that retail investors are also inclined to herd at the style level (Kumar, 2009; Jame and Tong, 2014). Institutions may also engage in styles that attract attention to cater to retail investor demand (Barberis and Shleifer, 2003; Lou, 2012). Therefore, if retail investors' trading behavior aligns more with recent returns of some styles, it might signify a higher degree of style chasing and hence a stronger price impact for these styles. Analogous to the previous section, we estimate the propensity of retail style trading (PRST) by monthly cross-sectional regressions:

$$RetailOib_{i,t+1} = a_t + PRST_{style,t} R_{i,t}^{style} + b_t X_{i,t} + \varepsilon_{i,t+1}, \tag{4}$$

where $RetailOib_{i,t+1}$ is the monthly retail order imbalance of stock i, $R_{i,t}^{style}$ is the style return in the last month, and $X_{i,t}$ is the vector of control variables. We obtain retail trading volume data from the WRDS-TAQ Millisecond Tools database.[19] The daily retail order imbalance is computed as the volume of retail buys minus the volume of retail sells, divided by the total volume of retail buys and sells. Then, the monthly retail order imbalance for each stock is calculated by aggregating the daily retail order imbalances within a given month.[20]

Since retail trading data are limited and the order imbalance sample starts only in 2007, we use a cross-sectional approach to study the relationship between PRST and style effects. Specifically, we first calculate the average propensity of retail style trading ($\overline{PRST}$) for each style:

$$\overline{PRST}_{style} = \frac{1}{T} \sum_{t=1}^{T} PRST_{style,t} \tag{5}$$

and then conduct a cross-sectional regression:

$$\mathbb{E}[R_{style}] = \alpha + \beta_1 \overline{PRST}_{style} + \beta_2 \overline{PIST}_{style} + \beta_3 \overline{Comove}_{style} + \varepsilon_{style}. \tag{6}$$

The dependent variable, $\mathbb{E}[R_{style}]$, is the average style strategy return. If retail investors' stronger response to past style returns is a signal of heightened style chasing, then we should

[19] Retail trades are identified through the Boehmer et al. (2021) algorithm in this database. For more details on the WRDS retail trading data, please refer to Wharton Research Data Services, `https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-intraday-indicators/`.

[20] Similar to equation (2), control variables ($X_{i,t}$) include stock i's monthly return, the cumulative one-year return (skipping the most recent month), firm size, the book-to-market ratio, idiosyncratic volatility, gross profitability, and the investment-to-assets ratio.

expect a positive estimate of β_1. We also control for the average propensity of institutional style trading ($\overline{PIST}_{style}$) and the average comovement ($\overline{Comove}_{style}$).

Table 5 presents the results of cross-sectional regressions. It shows that the estimated coefficient on the average PRST ($\hat{\beta}_1$) is positive and significant. For instance, column (1) of Panel A suggests that a one standard deviation increase in average PRST implies an increase in the average style strategy return of 3.4 bps (t=2.42). In columns (3) to (6), we control for institutional trading and comovement. Consistent with previous results, the estimated coefficients on the average PIST ($\hat{\beta}_2$) and the average comovement ($\hat{\beta}_3$) are positive and highly significant. Nevertheless, the average PRST still exhibits a positive and significant association with style strategy performance. In Panel B, we use the annualized Sharpe ratio of style strategies as the dependent variable and find similar results.

3.4 Characteristic attractiveness and style strategy returns

In Section 2.3, we show that the style-derived pricing effect does not rely on the predictive ability of the underlying characteristics. Under the style investing view, investors are drawn to and extrapolate from recent, transitory price movements rather than trading established return "anomalies." For example, when value stocks outperform growth stocks, the value category attracts attention and induces style-level trading. Similarly, when growth stocks substantially outperform, flows tilt toward the growth category. In both cases, heightened style demand amplifies the price impact and lifts the return of the style strategy based on book-to-market. In other words, style investors chase price trends without relying on the characteristic's own predictive ability. This finding implies that style effects should be stronger as the *magnitude* of past characteristic returns increases, since the style becomes attractive.

To test this prediction, we define the characteristic return spread (CRS) for each style as the absolute value of the monthly long-short strategy return of the corresponding characteristic. For instance, CRS for the value style is calculated as the magnitude of the return spread between the top and bottom book-to-market decile portfolios. Then, we conduct the following regression to examine the relationship between CRS and style effects:

$$R_{style,t+1} = \alpha + \beta_1 CRS_{style,t} + \beta_2 Comove_{style,t} + \beta_3 PIST_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}, \quad (7)$$

where we control for comovement and the propensity of institutional style trading studied in

previous sections. If investors chase style performance rather than speculating on anomaly returns, then we should expect a positive $\hat{\beta}_1$; moreover, the raw characteristic return without taking the absolute value should exhibit no predictive power for style effects.

Table 6 reports the regression results. It shows that CRS is a strong predictor for style strategy returns in both the cross section and time series. The first three columns of Panel A suggest that a one standard deviation increase in lagged CRS is associated with a subsequent increase in style returns of around 7.7 bps. Controlling for the influence of comovement and PIST does not alter this finding. In addition, columns (4) to (6) of Panel A show that the estimated coefficients on Comove and PIST remain significant and are comparable to previous estimates. This result suggests that CRS captures incremental information describing the price impact of style investing.[21]

Panel B of Table 6 tests a variety of alternative measures. First, we use raw characteristic returns instead of absolute values. The estimated coefficient is minor and insignificant (t=0.74). Second, we adjust the signs of characteristic returns based on the predictive power of characteristics, ensuring that their expected values are always positive.[22] Even after this adjustment, the signed characteristic returns exhibit no predictive power for style effects. Third, we find that style strategies display weak autocorrelations as lagged style strategy returns do not predict future returns. As a placebo test, we also use the absolute value of past style returns or the standard deviation of portfolio returns across characteristic deciles. Columns (4) and (5) of Panel B show that these variables do not explain style effects.

Finally, one might worry that higher CRS implies that the sorting variable used in forming style strategies exhibits a larger spread, thus the relation documented in this section might arise mechanically. A crucial difference between CRS and the sorting variable (i.e., the average return of style peer stocks) spread is that CRS is computed by first sorting stocks based on *characteristics* and then using the return spread between extreme characteristic deciles. In contrast, style strategies are formed by sorting stocks based on style peer *returns*,

[21]In addition, CRS differs from comovement and investors' propensity to trade (i.e., PIST and PRST) in that time variation matters more in the predictive ability of CRS, and an unconditionally high CRS does not necessarily imply stronger style returns. This is because CRS captures transient fluctuations in style attractiveness, whereas a pure cross-sectional regression loses information on the variation in CRS over time. Indeed, in cross-sectional regressions in the form of equation (6), the average CRS does not significantly correlate with the average style strategy return after accounting for the average comovement.

[22]We consider this adjustment since we have utilized high-minus-low portfolios to define characteristic returns. For example, prior research shows that asset growth (AG) is negatively associated with future returns; consequently, we multiply the characteristic return series based on AG by -1. The final sample size is smaller than the baseline case (Panel A of Table 6) due to the exclusion of characteristics without clear predictive ability (i.e., the "placebos" in the Chen and Zimmermann (2022) database).

and a higher style signal does not necessarily correspond to a larger characteristic value. The last column of Panel B shows that the style signal spread is indeed positively correlated with future style strategy returns, but the estimate is insignificant (t=1.50); the estimated slope on CRS remains positive (0.063) and statistically significant (t=3.82).

3.5 Evaluating implementation complexity using LLMs

Characteristics vary in complexity, which is crucial for implementing trading strategies. For instance, characteristics such as the book-to-market ratio and momentum are conceptually clear, easily computed, readily accessible, and widely acknowledged. In contrast, characteristics that combine multiple indicators and require multi-stage estimations tend to be more challenging to understand, difficult to calculate, and less commonly adopted in practice. In addition, institutions also have incentives to employ less complex characteristics as they facilitate risk management and performance attribution while appealing to clients' attention. Therefore, less complex characteristics are more likely to gain broader adoption in style investing, thereby yielding stronger price impacts.

A virtue of studying complexity is that it also allows us to partially distinguish style investing from the underreaction channel. It is possible that the profits of these style strategies partly stem from investors underreacting to common news shared by firms with similar fundamentals. If such underreaction were the main driving force behind our findings, however, higher complexity should imply stronger performance of style strategies. This is because highly complex characteristics tend to be less visible, more difficult to trade, and harder to comprehend. Therefore, underreaction-driven effects should be positively associated with complexity as they require more cognitive resources.[23] In contrast, style investing suggests that characteristics with lower complexity are more favorable and should thus generate stronger pricing effects.

Complexity is challenging to quantify empirically. We attempt to address this issue by leveraging recent developments in large language models (LLMs) to assess the complexities of characteristics.[24] Specifically, we obtain detailed textual descriptions of each characteristic

[23]This reasoning aligns with existing literature. For instance, You and Zhang (2009) document stronger investor underreaction to more complex 10-K reports, while Miller (2010) finds that longer and less readable financial filings inhibit trading activity.

[24]Research on using LLMs to extract information, generate evaluations and forecasts, and simulate human belief and behavior is growing rapidly, showing that LLMs exhibit exceptional capabilities across various tasks. See, for example, Chen et al. (2022b); Bybee (2023); Kim et al. (2023); Gabaix et al. (2023); Jha et al.

from the OSAP website. The descriptions provided by Chen and Zimmermann (2022) contain definitions, data requirements, and construction methods of characteristics. We then prompt OpenAI's ChatGPT-4o with these descriptions and ask it to evaluate complexity by assigning each characteristic a score, ranging from 1 to 3, with higher scores indicating greater complexity. Figure 7 illustrates the prompt used in this section. We use the default parameter settings of ChatGPT in our analysis. To account for potential variability and randomness in ChatGPT's responses, we submit the same prompt independently for 100 rounds and calculate the average complexity score for each characteristic.[25]

To examine the relationship between implementation complexity and style effects, we conduct the following cross-sectional regression:

$$\mathbb{E}[R_{style}] = \alpha + \beta Complexity_{style} + Controls + \varepsilon_{style}, \tag{8}$$

where the dependent variable ($\mathbb{E}[R_{style}]$) is the average style strategy return. The main independent variable of interest, $Complexity_{style}$, represents the average complexity score from ChatGPT's evaluations of the underlying characteristics in implementing trading strategies. Column (1) of Panel A in Table 7 reports the univariate regression results. The estimated β is negative and highly significant (t=-5.80), indicating that characteristics that are more difficult to implement in trading strategies are indeed associated with weaker style effects.[26] Economically, a one-unit increase in the complexity score corresponds to about a 0.21% decrease in the average style strategy return. This finding suggests that implementation barriers, such as complexity, limit the extent to which a style can impact prices.

An important confounding factor is that characteristics within the same economic category might share similar complexity levels. For example, valuation ratios typically

(2024); and Kim et al. (2024).

[25]To provide intuition for the complexity measure, consider the following examples. Characteristics like the book-to-market ratio (book value divided by market capitalization) and momentum (cumulative one-year return) receive relatively low average complexity scores of 1.70 and 1.56, respectively. In contrast, the predicted analyst forecast error measure developed by Frankel and Lee (1998), which requires obtaining consensus forecast data and estimating a residual model, receives a substantially higher average complexity score of 2.50. While the predicted analyst forecast error is theoretically well grounded and academically important, its implementation complexity creates meaningful barriers for market participants due to the extensive data requirements, sophisticated econometric estimation, and ongoing maintenance needs.

[26]The prompt depicted in Figure 7 also includes confidence levels for the assigned complexity scores. We find that the regression results remain quantitatively similar when observations are weighted by average confidence levels or when using Complexity × Confidence level as the independent variable. Therefore, we focus solely on the complexity score in the analysis.

involve dividing accounting terms by market capitalization, while profitability calculations commonly involve computing revenues and costs. Therefore, we include economic category fixed effects in column (2). The estimated β remains robust under this specification.

Data requirement is another dimension that might affect complexity. For instance, the book-to-market ratio primarily relies on accounting data, momentum is derived from stock price data, and analyst forecasts require data from IBES. Thus, we also incorporate fixed effects for data categories. Additionally, we address the potential concern that complexity may correlate with the journal in which the corresponding paper was published. In Panel A of Table 7, columns (3) to (5) show that the negative correlation between complexity and style strategy performance remains consistent across different fixed effects specifications. Finally, regressions in Panel B control for variables studied in previous sections. The estimated coefficient on complexity remains negative across all specifications.[27]

3.6 Exhaustive search over accounting ratios

The preceding analyses establish that style-based return predictability is pervasive across the 312 characteristics designed as investment signals. Styles exhibiting excessive return comovement, intensive investor participation, and greater accessibility display stronger pricing effects. These heterogeneity results align well with both economic theory and real-world financial market practices.

If the style investing mechanism is genuinely pervasive, then economically meaningful firm attributes relevant to investment practice should generate style effects, even if they have not been identified as return predictors. Financial variables lacking economic substance, however, should not exhibit significant predictability, as they are unlikely to be used in portfolio construction.[28] This section conducts an exhaustive search by constructing style signals from all pairwise ratios of Compustat accounting items.

We begin with the full set of annual Compustat items related to firm fundamentals.[29]

[27]The negative correlation between complexity and the style effect is also valid when using the Sharpe ratio to measure strategy performance. In a placebo test, we further show that complexity relates *insignificantly* to the performance of characteristic-based strategies. These results are reported in Appendix Table A1.

[28]There are, of course, rare cases in which characteristics with limited economic content attract investor attention. For example, Green and Hwang (2009) show that investors trade categorically based on nominal share price. Nevertheless, most arbitrary financial ratios are generally not central to investment practice.

[29]Specifically, we retain decimal-type variables from standard financial statements and exclude adjustment factor-related items such as the share adjustment factor and the currency translation rate, per-share variables

For every pair of Compustat items (X, Y), we compute the ratio X_i/Y_i and the change in the ratio $\Delta(X_i/Y_i)$ for each firm i at the end of June. We require at least 500 stocks with non-missing ratio values each year, exclude ratios with fewer than 10 years of available data, and require a minimum of five stocks per group in each formation period. These filters yield 42,334 unique ratio-based characteristics. For each ratio, we sort stocks into 25 groups at the end of each June and hold the resulting classification for the subsequent 12 months. For each stock, the style signal is calculated as the value-weighted average monthly return of other stocks in the same group. We then form decile portfolios each month based on these style signals and construct a long-short strategy that buys stocks in the top decile and sells those in the bottom decile.

The upper panels of Figure 8 present the performance of the 42,334 style strategies. In sharp contrast to the main results based on anomaly characteristics, the vast majority of artificial ratios do not generate style effects. Only about 16% of strategies yield significantly positive returns ($t \geq 1.96$). Strategy returns are also modest, with a mean (median) abnormal return of 0.12% (0.11%) per month. These patterns are consistent with the hypothesis that most arbitrary accounting ratios lack the economic content necessary to attract coordinated investor attention.

Moreover, the significant strategies cluster around economically meaningful variables rather than arising at random. We classify Compustat items into accounting categories and examine the contribution of each category to the set of significant strategies.[30] Because each strategy involves a ratio of two items, a given strategy may span two distinct categories; the analysis therefore reports non-exclusive category contributions. The lower panel of Figure 8 focuses on the 10 most prominent categories. We find that ratios with significant style effects are concentrated in categories that attract investor attention, such as earnings, assets, and market price-related items. These ratios capture dimensions central to investment practice, whereas variables based on obscure or rarely used accounting items exhibit little style effects. The contrast between the high incidence of significance among a small set of economically salient ratios and the near absence of significance among the large majority of arbitrary ratios is consistent with the view that style-induced demand influences asset prices.

---

such as book value per share and earnings per share, and share-related variables such as shares outstanding and dilution adjustments.

[30] We manually classify items into 27 accounting categories, including assets, cash flow, comprehensive income, debt, deferred items, depreciation and amortization, dividends, earnings, employees, equity, gains and losses, inventory, investment, liabilities, mortgage and securitization, operating expenses, PP&E, pension, preferred stock, price and market, R&D, revenue and cost, special items, stock options, tax, tax uncertainty, and others.

3.7 A placebo test based on random styles

The accounting ratio analysis shows that style effects arise selectively from economically meaningful firm attributes. As a complementary test, we now strip away the economic content by constructing style groups from purely random variables that no investor would plausibly follow. It is reasonable to expect that artificially constructed style signals, lacking an economic foundation, should demonstrate minimal predictive power.

We implement this placebo test in two ways. First, we generate style groups by simply assigning two random numbers to each stock at the end of June. Stocks are categorized into 5×5 portfolios by sorting on these assigned numbers. Following the methodology used throughout the paper, we compute style signals as the value-weighted average monthly returns of other stocks within the same randomly assigned group. We then form decile portfolios based on these signals and evaluate long-short strategies that buy stocks in the top decile and sell stocks in the bottom decile. Panels (a) and (b) of Figure 9 depict the performance distribution of these random style-based strategies. As expected, the t-statistics are centered around zero, with more than 93% falling below the conventional significance threshold of 1.96 in absolute value.

Second, purely random groupings ignore the temporal persistence inherent in real firm characteristics. To address this concern, we construct pseudo-characteristics that replicate the persistence structure of real characteristics but carry no economic content. Specifically, we model each pseudo-characteristic as an AR(1) process:

$$X_{i,t} = \rho X_{i,t-1} + \epsilon_{i,t}, \tag{9}$$

where $X_{i,t}$ represents the characteristic value of i in June of year t. We estimate the persistence parameter ρ and the volatility σ of the noise term $\epsilon_{i,t}$ for each of the 312 real characteristics.[31] The resulting estimates span $\rho \in [-0.26, 0.98]$ and $\sigma \in [0.18, 1.00]$. We form a 15×15 grid over these intervals, yielding 225 (ρ, σ) pairs. For each pair, we simulate 100 independent rounds. Each round initializes stock characteristics from a standard normal distribution and updates them annually via equation (9). Stocks are then categorized into 25 portfolios by sorting on the simulated characteristic value each June. Style signals and

[31] Specifically, we standardize each characteristic cross-sectionally to have zero mean and unit variance. We then estimate a panel regression of standardized June values on their one-year lags, yielding estimates of ρ and σ for that characteristic. Repeating this procedure for all 312 characteristics produces 312 estimates of ρ and 312 estimates of σ.

corresponding trading strategies are constructed following the same methodology as before. This procedure generates 22,500 style-round observations.

Panel (c) of Figure 9 presents the t-statistic distribution across the 22,500 pseudo-characteristic style-rounds. Consistent with the random-number test, approximately 93.7% of strategies fail to achieve statistical significance at conventional levels. In Panel (d), we calculate for each style the fraction of 100 rounds yielding $t \geq 1.96$. The rate of significance is low throughout and shows no systematic pattern with respect to either persistence or volatility, indicating that the style pricing effect does not arise mechanically from specific dynamics of the underlying characteristic.[32] Collectively, these placebo tests provide evidence that the documented style-based return predictability is unlikely to be an artifact of statistical noise or mechanical persistence in characteristics. Rather, its pervasiveness points to the price impact of style-driven trading.

3.8 Discussion on alternative explanations and related patterns

The style signal employed throughout this paper aggregates the recent return of peer stocks sharing a common characteristic-based classification. On the other hand, a growing literature on factor momentum documents that characteristic-based factors exhibit a positive short-run autocorrelation (Ehsani and Linnainmaa, 2022; Arnott et al., 2023), implying that a factor's recent outperformance tends to persist into the next period. In particular, factor momentum implies that firms in the smallest size decile are likely to outperform firms in the largest size decile when they have done so over the prior year, a finding similar in spirit to our style strategies at first glance.

However, style strategies differ from factor momentum in that the former compares peer performance across characteristic-sorted portfolios, whereas factor momentum focuses on the extreme (long and short) portfolios. Table 8 reports the distribution of characteristic ranks across style signal-sorted deciles. We find that the distribution is fairly uniform, and most stocks in the extreme style signal deciles are not drawn from the extreme characteristic deciles. In particular, our style portfolio strategies only involve about 23% of the stocks in the extreme decile portfolios, which is only slightly higher than the 20% uinform benchmark

[32] If anything, the few instances of high significance rates are observed among pseudo-characteristics with moderate-to-high persistence and sufficiently low volatility. These cells, however, comprise a tiny fraction of the (ρ, σ) grid and lie outside the parameter region occupied by most real characteristics. Therefore, any mechanical persistence of near-constant group assignments cannot explain the pervasiveness of the style effects.

and distinct from the traditional factor momentum analysis which only uses stocks with extreme characteristics. Thus, the predictive ability of style signals should not be attributed solely to momentum in the long- or short-leg characteristic portfolios. After all, in terms of stocks involved in trading, style portfolio strategies are distinct from the factor momentum strategies.

In addition, Appendix Figure A2 shows the t-statistic distribution of style strategies after controlling for factor momentum (Ehsani and Linnainmaa, 2022; Arnott et al., 2023). More than half (53%) of the 312 styles continue to generate significantly positive returns, indicating that factor momentum alone cannot fully account for our results. While this overlap confirms a statistical connection, factor momentum by itself does not reveal the underlying mechanism. More importantly, the salient question is what economic force generates an autocorrelation in factor returns. We discuss below how the documented style effect may, in turn, partially explain factor momentum.

At least three channels may be responsible for both the style effect and momentum in factors. First, a *rational* explanation suggests that characteristics could capture exposure to common fundamental risks. To the extent that such exposures are persistent, a positive return autocorrelation may arise as compensation for risk. Second, investors may *underreact* to fundamental news shared by firms with similar characteristics because of limited attention or processing constraints (Hong and Stein, 1999; Peng and Xiong, 2006; Cohen and Frazzini, 2008). Mispricing may persist since arbitrageurs are often delayed by fractions (Shleifer and Vishny, 1997; Duffie, 2010). Under this view, the style signal captures neglected news, and the ensuing predictability represents sluggish convergence to fundamentals. Third, in the model of Barberis and Shleifer (2003) and related frameworks (e.g., De Long et al. (1990)), investors allocate capital at the category level and chase recent style performance. This *positive feedback trading* creates common demand shocks that generate an autocorrelation in factor returns. Under this view, return predictability reflects continued overreaction (Daniel et al., 1998) whereby institutions destabilize prices.

These channels are not mutually exclusive and likely coexist in driving the pervasive style effect and factor momentum. Nevertheless, the cross-style heterogeneity documented in this paper provides a valuable opportunity to assess their relative importance. A risk-based explanation may help account for average returns, but it offers less direct guidance on the heterogeneity tests; we thus focus on discriminating among the behavioral channels.

The positive relationship between the propensity of institutional style trading (PIST)

and future style-strategy returns, documented in Section 3.2, provides sharp discriminating evidence. The underreaction hypothesis yields a clear directional prediction. When institutional trading aligns with style signals, it accelerates the incorporation of neglected fundamental news, thereby *attenuating* return predictability (Cohen and Frazzini, 2008; Ben-Rephael et al., 2017). In contrast, if the return predictability stems from positive feedback trading, then institutions *amplify* mispricing through coordinated style-level demand (Brunnermeier and Nagel, 2004; Griffin et al., 2011). Taken together, the PIST evidence favors the continued overreaction channel over the alternatives.

The complexity dimension in Section 3.5 provides a second discriminating test. Under the underreaction channel, complex characteristics are harder to perceive and process, which should intensify investor neglect and produce *stronger* underreaction-driven effects (You and Zhang, 2009). The positive feedback-trading channel posits, however, that less complex characteristics are more accessible, more widely adopted, and more likely to attract style-level attention. Higher complexity should therefore be associated with less prevalent style investing and *weaker* pricing effects. The negative complexity-style effect relationship aligns with the last prediction and is difficult to reconcile with the other two.

In sum, while our style results could, in principle, be consistent with a rational framework, the heterogeneity tests are more consistent with the continued overreaction due to style investing. Factor momentum (Ehsani and Linnainmaa, 2022; Arnott et al., 2023) has been documented and examined from a statistical and methodological perspective (Leippold and Yang, 2021; Fan et al., 2022; Cakici et al., 2025), yet the underlying economic mechanism remains largely unexplored. Rather than collapsing factors into a single composite strategy, this paper disentangles the drivers of cross-sectional variation in return predictability. Although various predictability patterns are statistically entangled, the heterogeneity results provide a coherent economic narrative. In this sense, the findings can offer a potential explanation for, and evidence on, factor momentum, thereby complementing existing studies.

4 Dimension of Style Effects

Styles naturally exhibit correlations. For instance, a trading strategy tilted toward high-tech firms tend to load on companies with similar investment activity and valuation ratios. This section characterizes the correlation structure across styles. Building on these results, we investigate the role of dimensionality in unveiling return predictability from style investing.

4.1 Correlations between styles

As the empirical asset pricing literature has discovered a large set of cross-sectional anomalies, it remains an unsolved question as to which firm characteristics truly provide independent information about expected returns (Cochrane, 2011). Recent studies, however, point out that characteristics contain distinct information. Green et al. (2013), McLean and Pontiff (2016), Yan and Zheng (2017), Chen and Zimmermann (2022), and Chen and McCoy (2024) document that the correlations between characteristics and portfolio returns are generally close to zero. Kozak et al. (2020) show that the redundancy among predictors is small, and a characteristics-sparse model is insufficient to explain cross-sectional returns. Since most characteristic-derived style signals demonstrate significant predictive ability for returns, it is important to examine the interdependence of styles.

Figure 10 shows the distributions of pairwise correlations between styles. For style signals, we first calculate cross-sectional correlation coefficients and then take time-series averages; for style strategies, we simply compute the full-sample pairwise correlations between long-short portfolio returns. In sharp contrast to characteristic-based results, we find that style-based predictors and strategy returns are highly correlated. The pairwise correlations among style signals cluster around 0.40, whereas those among strategy returns cluster around 0.60.[33]

To inspect the commonality in style returns, we extract the principal components (PCs) from an eigenvalue decomposition of the covariance matrix of style strategies. We restrict attention to styles whose underlying characteristic data begin in June 1980 or earlier and whose full-sample strategy returns are significant at the 5% level.[34] Following Kozak et al. (2018), we also conduct time-series regressions of each style strategy on the first K PCs. The second column of Table 9 reports the average R^2 for PCs 1 to 10. The first PC alone explains 57.6% of the time-series variation in style returns. As a comparison, PCs with lower eigenvalues provide minor explanatory power, with an average R^2 of 66% when the first five PCs are included in regressions. The third column reports the amount of variance explained by the first K PCs. Likewise, we find that the first PC explains a substantial portion (58.4%) of the time-series variation in strategy returns. Figure 11 graphically presents the cumulative ratio of the total variance of style strategies explained by PCs.

[33]Note that the style interdependence should not be solely constrained by the correlations between characteristics. To illustrate this, consider two characteristics, denoted as x and y, satisfying a quadratic relation: $y_{i,t} = a + bx_{i,t}^2 + \varepsilon_{i,t}$, with $Corr[x_{i,t}, y_{i,t}] \sim 0$. If we group stocks based on their x values, those within the same group are likely to share similar y values, even though the linear correlation between x and y is minimal.

[34]After applying these criteria, a total of 273 styles remain for examination.

The first PC places positive weights on all styles, with the factor loading ranging from 0.084 to 0.017 and a standard deviation of 0.012. The solid line in Figure 11 visualizes the factor loadings of PC1 in descending order. The factor loading gradually declines for the first 250 styles and diminishes more steeply thereafter. The relatively flat pattern of the curve suggests that the first PC is not dominated by a small set of styles; most styles provide comparable contributions to the composition of PC1. Column 4 of Table 9 reports the factor loadings of PC1 on the first 10 styles in descending order. Consistent with their prevalence in investment practice, styles from categories such as value, investment, volatility, and profitability exhibit greater importance in characterizing the underlying latent factor driving style strategy returns.

4.2 High-dimensional styles and return predictability

In this section, we examine the role of dimensionality in style pricing. The fact that (1) the first PC explains a substantial portion of the time-series variation in style strategy returns and (2) the first PC puts positive weights on all styles, suggests that it is necessary to combine information from multiple characteristics to identify style groups. To this end, we adopt a standard machine learning algorithm, k-means clustering, to construct style signals in a high-dimensional setting.

Consider N stocks $(\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N)$, where each stock is featured by d characteristics. The k-means clustering partitions the stocks into K clusters $\mathbb{C} = \{C_1, C_2, ..., C_K\}$ by minimizing the within-cluster sum of squares (Hastie et al., 2009):

$$W(\mathbb{C}) = \sum_{k=1}^{K} \sum_{\mathbf{x} \in C_k} \|\mathbf{x} - \mathbf{m}_k\|^2, \tag{10}$$

where $\mathbf{m}_k$ is a d-dimensional mean vector of observations in the kth cluster. To solve the optimization problem, the algorithm initializes centroids $(\mathbf{m}_1, \mathbf{m}_2, ..., \mathbf{m}_K)$ and iterates two steps until convergence. In the first step, each stock is assigned to the closest cluster mean; in the second step, each mean vector $\mathbf{m}_k$ is updated as the mean of the currently assigned observations. In the context of style investing, we use k-means clustering to identify style clusters and then define the style signal as the value-weighted average return of a stock's style peers. By choosing different values for d, we examine how the return predictability varies with the style dimensionality.

For a given number of dimensions d, an ideal implementation would be to enumerate all possible combinations and compute the average result. For example, consider 3 characteristics, (A, B, C), and $d = 2$. Then, we have 3 styles to be examined: (A, B), (A, C), and (B, C). However, the computational cost becomes extremely high as the set of characteristics expands. To illustrate, choosing just 5 dimensions from a pool of 20 characteristics results in the generation of 15,504 styles. As such, it becomes computationally intensive when dealing with examinations of over 200 underlying characteristics.

We use a heuristic procedure to guide our empirical examination. Specifically, we rank individual styles in descending order based on their loadings on the first PC, which are calculated in the previous subsection. Then, we choose the first d variables (along with firm size) to construct the d-dimensional style and the associated return signal. For example, when $d = 2$, we use size, CF (cash-flow-to-market), and IdioVolCAPM (idiosyncratic volatility) and apply the k-means clustering each June to identify style groups.[35] Analogously, the style signal for individual stocks is calculated as the value-weighted average return of other stocks within the same group. It is worth noting that while the computation of PCs and factor loadings relies on full-sample results, our approach does not directly use quantitative information. Rather, we rely solely on the extraction of ranks to guide the determination of which styles are incorporated in the construction process for a specific number of dimensions.

Figure 12 reports the performance of high-dimensional style strategies graphically. Similar to our baseline analysis, we form decile portfolios based on style signals and calculate average returns to long-short strategies. The main difference is that the signal is constructed in a high-dimensional style setting. The two panels depict the average monthly returns and annualized Sharpe ratios of strategies as a function of the number of dimensions (d) used in identifying styles. Notably, the performance of strategies tends to increase in the number of style dimensions. Starting from lower dimensions where $d < 30$, the derived style strategies yield a value-weighted monthly return of over 1% and a Sharpe ratio of above 0.5 in general. The improvements are economically large as d exceeds 150, under which the value-weighted long-short portfolio earns a return of over 2% and a Sharpe ratio of around 1. The curves become flat for $d > 200$. The potential value-weighted (equal-weighted) annualized return of a high-dimensional style strategy is around 29.2% (38.8%) and has an annualized Sharpe ratio of around 1.16 (1.77).

[35] In each computation, we standardize all characteristics cross-sectionally by mapping their ranks to the interval $[0, 1]$. For missing values, we employ imputation with cross-sectional medians (Gu et al., 2020). The results remain qualitatively similar when using alternative approaches, such as standardizing characteristics to zero mean and unit variance.

The result implies that, while style returns are positively correlated, large economic gains can be obtained by increasing the number of characteristics used in defining styles. This finding aligns with recent studies such as Chen and McCoy (2024) and Kozak et al. (2020) that point to a high dimensionality feature of expected stock returns. Since style investments are complicated and diverse in practice, increasing the number of characteristics in style construction provides incremental information. By more accurately approximating stocks' potential style embeddings, machine learning approaches can help expose the return predictability driven by the price impact of style investing.

4.3 Styles from principal components of characteristics

It has been shown that, despite the high correlation among individual styles, a characteristic-sparse model falls short in summarizing return predictability. While investment styles are diverse and heterogeneous, characteristics exhibiting interdependence might lead to correlated capital allocation. A strategy centered on the book-to-market ratio tends to resemble one based on the earnings-to-price ratio, while an investment focused on return-on-assets typically coordinates with one targeting operating profits. Therefore, principal components of characteristics, which capture dependencies along individual dimensions, might offer a relatively concise depiction of the underlying cluster structure.

We modify the previous examination by first rotating stocks into the PC space before constructing style groups. To achieve this, each June, we calculate the principal components of characteristics and then apply k-means clustering using the first d PCs as inputs. The style signals and long-short strategies are formed analogously. Figure 13 depicts the performance of PC style strategies as a function of the number of PCs employed. In sharp contrast to the results presented in Figure 12, a PC-sparse model performs equally well as high-dimensional models. The value-weighted return of a strategy with 6 PCs is 2.03% per month, while the 8-PC style strategy yields 2.29% (or 27.5% annualized). As the number of PC dimensions increases, the performance curves remain nearly flat. A similar trend is noted in the strategy Sharpe ratios.

The fact that a PC-sparse model captures the majority of return predictability aligns neatly with the findings of Kozak et al. (2020). In particular, Kozak et al. (2020) demonstrate that while individual characteristics exhibit little redundancy, the PC space displays a higher degree of sparsity: a stochastic discount factor (SDF) with 4 PCs performs quite well in describing portfolio returns based on 55 characteristics, and an SDF with 6 PCs achieves

almost maximum out-of-sample R^2 for portfolios based on 80 financial ratios. In the context of style returns, Figure 12 indicates that a large number of characteristics is necessary to reveal the potential return predictability. Nevertheless, Figure 13 suggests that a sparse representation in the PC space can capture similar pricing implications.

In the absence of near-arbitrage opportunities, cross-sectional variation in expected returns should be explained by common factors in return covariances (Kozak et al., 2018). In the context of style investing (Barberis and Shleifer, 2003), such common factors manifest as a consequence of investors trading at the style level and chasing trends.[36] Since individual characteristics are noisy proxies, PCs of characteristics provide a parsimonious basis for capturing the latent cluster structure and the resulting coordinated style demand. As such, styles derived from high-eigenvalue PCs contribute substantially to the observed return predictability.

5 Additional Tests

This section assesses the robustness of the main result, including the predictive ability of residual style signals, alternative specifications of style strategies, within- and cross-industry results, and alternative signal constructions. We also extend the analysis to two additional characteristic datasets to mitigate concerns about potential data noise.

5.1 Residual style signals

Previous studies document that stocks within the same style group exhibit excess comovement (Barberis et al., 2005; Green and Hwang, 2009; Boyer, 2011). While we show that comovement is an important determinant of style strategy returns, the general positive correlation between style signals and focal firms' contemporaneous returns could weaken estimates of return predictability. Specifically, it is well accepted that stock returns tend to reverse at short horizons (Lehmann, 1990; Lo and MacKinlay, 1990). Thus, orthogonalizing the signal with respect to the contemporaneous return should sharpen its predictive power.

We compute residual style signals as the residuals from monthly cross-sectional regressions of each style signal on the focal firm's contemporaneous return. Appendix Table

[36]Recent studies such as Clarke and Linn (2022) indeed show that characteristics are important in explaining the covariances of stock returns.

A2 reports the portfolio results using residual style signals. The number of strategies with significant value-weighted returns increases, ranging from 279 to 294 (depending on the benchmark model), indicating that over 89% of styles exhibit predictive ability for returns. The average strategy returns increase by around 5 bps, with at least 85% of them attaining statistical significance at the 1% level. Overall, purging the reversal effect in focal stocks' returns helps to strengthen the performance of style strategies.

5.2 Alternative portfolio specifications

The main results of this paper rely on decile portfolios formed by style signals with a share price cutoff of \$1. As demonstrated by Hou et al. (2020), most asset pricing anomalies fail to earn significant returns after controlling for microcap effects and are sensitive to choices of breakpoints and weighting schemes. In this section, we examine the robustness of style pricing through several alternative portfolio specifications: (1) using quintile portfolios instead of decile portfolios; (2) requiring a share price of at least \$5 instead of \$1; (3) using quintile portfolios with a share price cutoff of \$5; (4) using NYSE breakpoints when forming portfolios; (5) using NYSE breakpoints with a share price of at least \$5; (6) excluding stocks in the bottom two deciles of the monthly market capitalization distribution (NYSE breakpoints).

Appendix Figure A1 reports the distribution of t-statistics of style strategies under these specifications. Consistent with our main finding, over 75% of style signals exhibit significant predictive ability, as the 25th percentile is generally larger than 2. Moreover, over half of style strategies earn positive returns with a t-statistic of at least 3, even after imposing strict liquidity adjustments to the sample. In sum, these results show that the pervasive predictive power of style signals is robust to variations in portfolio construction and is not driven by microcap-related issues.

5.3 Within- and cross-industry predictability

Industry-based styles are common. Choi and Sias (2009) show that institutions herd to industry styles in a way consistent with Barberis and Shleifer (2003); Jame and Tong (2014) find industry-wide style investing behavior among retail investors. Since industries are composite representations of multiple characteristics, industry portfolios can subsume certain styles. Accordingly, the predictive power of style signals might weaken once industry

peers are removed. By contrast, constructing styles strictly within industries should sharpen the result, as conditioning on industry effectively adds dimension to the style identification process, which (as shown in Section 4.2) enhances the predictive power of style signals.

Appendix Figure A3 reports the within- and cross-industry return predictability. Specifically, we assign stocks to industries based on the four-digit SIC codes. Then, we calculate style signals as the value-weighted average returns of style peers within the same industry or in different industries. Consistent with our conjecture, within-industry signals exhibit a stronger predictive ability for returns. Over 70% of the 312 style strategies earn a positive return with a t-statistic above 3. For strategies based on cross-industry signals, the result is generally weaker. Nevertheless, more than half of the 312 styles still display return predictability significant at the 5% level. These findings affirm that industry forces contribute to characteristic-based styles, but the pervasive return predictability cannot be attributed solely to industry-level style investing.

5.4 Alternative constructions and other characteristic datasets

We further assess the robustness of the style-based pricing effect through several other variations in empirical specifications. First, we have used the size-characteristic grids in the main analysis to identify styles, which are more realistic than single-dimensional constructions in mimicking real investment practice. We test a simpler one-way sort construction. Specifically, each June and for each characteristic, we sort stocks into 10 groups based on the characteristic and compute style signals as the value-weighted average returns of other stocks in the same decile.

Second, we address the potential concern regarding data quality. While the Chen and Zimmermann (2022) database is among the most comprehensive and increasingly used in empirical asset pricing, we supplement the analysis with two alternative datasets. The first comprises 53 characteristics (excluding size) used by Kozak (2020), and the second comprises 94 variables (excluding size and industry-adjusted size) used by Gu et al. (2020).[37] For each dataset, we examine the predictive ability of derived style signals with the same construction as applied to the Chen and Zimmermann (2022) database.

Appendix Figure A4 shows that using single-dimension styles still yields pervasive

[37]The datasets can be downloaded at Serhiy Kozak's website (`https://sites.google.com/site/serhiykozak/data`) and Dacheng Xiu's website (`https://dachxiu.chicagobooth.edu/`), respectively. We are grateful to them for making these data available.

predictability. The 25th percentile of the t-statistic distribution exceeds 2, implying that more than 75% of style strategies deliver statistically significant returns. For the Kozak (2020) and Gu et al. (2020) datasets, the evidence is even stronger. In each case, only two strategies fail to reach significance, and most strategies earn positive profits with t-statistics above 3. In fact, many variables in the Chen and Zimmermann (2022) database may not feature prominently in institutional investment universes, potentially explaining the comparatively weaker effects observed.

6 Conclusion

The asset management industry has grown substantially in recent decades, alongside increasingly sophisticated and diverse investment styles. Style-level asset allocation in turn exerts notable impacts on equity price dynamics. Through an extensive analysis of 312 firm characteristics, we document a pervasive pattern of return predictability arising from style investing. The empirical findings align closely with the theoretical framework of Barberis and Shleifer (2003). Predictability is more pronounced for styles characterized by several key features: heightened comovement, intensified institutional style trading, greater retail investor participation, extreme characteristic performance, and lower implementation complexity. These results would not have been attainable without the analysis of a large number of styles. They highlight the importance of high dimensionality in capturing the spectrum of price impacts associated with style investing.

This research also offers insights into modeling expected stock returns. The empirical asset pricing literature has identified numerous characteristics that directly predict cross-sectional return variations. This study presents an alternative approach to extracting price-relevant information via style groupings. Unsupervised learning techniques and advanced deep learning algorithms would enable the identification of complex, non-linear style patterns in high-dimensional spaces. This approach opens new possibilities for research in the field.

References

Agarwal, V., L. Jiang, and Q. Wen. 2022. Why do mutual funds hold lottery stocks? *Journal of financial and quantitative analysis* 57:825–856.

Arnott, R. D., V. Kalesnik, and J. T. Linnainmaa. 2023. Factor momentum. *The Review of Financial Studies* 36:3034–3070.

Asquith, P., P. A. Pathak, and J. R. Ritter. 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics* 78:243–276.

Barberis, N., and A. Shleifer. 2003. Style investing. *Journal of financial Economics* 68:161–199.

Barberis, N., A. Shleifer, and J. Wurgler. 2005. Comovement. *Journal of financial economics* 75:283–317.

Ben-David, I., F. Franzoni, B. Kim, and R. Moussawi. 2023. Competition for attention in the ETF space. *The Review of Financial Studies* 36:987–1042.

Ben-David, I., J. Li, A. Rossi, and Y. Song. 2022. Ratings-driven demand and systematic price fluctuations. *The Review of Financial Studies* 35:2790–2838.

Ben-David, I., J. Li, A. Rossi, and Y. Song. 2024. Discontinued positive feedback trading and the decline of return predictability. *Journal of Financial and Quantitative Analysis* 59:3062–3100.

Ben-Rephael, A., Z. Da, and R. D. Israelsen. 2017. It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies* 30:3009–3047.

Bessembinder, H., A. Burt, and C. M. Hrdlicka. 2021. Time series variation in the factor zoo. *Aaron Paul and Hrdlicka, Christopher M., Time Series Variation in the Factor Zoo (December 22, 2021)* .

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang. 2021. Tracking retail investor activity. *The Journal of Finance* 76:2249–2305.

Bowles, B., A. V. Reed, M. C. Ringgenberg, and J. R. Thornock. 2024. Anomaly time. *The Journal of Finance* 79:3543–3579.

Boyer, B. H. 2011. Style-related comovement: Fundamentals or labels? *The Journal of Finance* 66:307–332.

Broman, M. S. 2022. Naïve style-level feedback trading in passive funds. *Journal of Financial and Quantitative Analysis* 57:1083–1114.

Brunnermeier, M. K., and S. Nagel. 2004. Hedge funds and the technology bubble. *The journal of Finance* 59:2013–2040.

Bryzgalova, S., M. Pelger, and J. Zhu. 2025. Forest through the trees: Building cross-sections of stock returns. *The Journal of Finance* 80:2447–2506.

Buffa, A. M., and I. Hodor. 2023. Institutional investors, heterogeneous benchmarks and the comovement of asset prices. *Journal of Financial Economics* 147:352–381.

Bybee, L. 2023. Surveying Generative AI's Economic Expectations. *arXiv preprint*

arXiv:2305.02823 .

Bybee, L., B. Kelly, A. Manela, and D. Xiu. 2024. Business news and business cycles. *The Journal of Finance* 79:3105–3147.

Bybee, L., B. Kelly, and Y. Su. 2023. Narrative asset pricing: Interpretable systematic risk factors from news text. *The Review of Financial Studies* 36:4759–4787.

Cakici, N., C. Fieberg, D. Metko, and A. Zaremba. 2025. Factor momentum versus price momentum: Insights from international markets. *Journal of Banking & Finance* 170:107332.

Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of finance* 52:57–82.

Chen, A. Y., A. Lopez-Lira, and T. Zimmermann. 2022a. Peer-reviewed theory does not help predict the cross-section of stock returns. *arXiv preprint arXiv:2212.10317* .

Chen, A. Y., and J. McCoy. 2024. Missing values handling for machine learning portfolios. *Journal of Financial Economics* 155:103815.

Chen, A. Y., and T. Zimmermann. 2022. Open Source Cross-Sectional Asset Pricing. *Critical Finance Review* 11:207–264.

Chen, H.-L., and W. De Bondt. 2004. Style momentum within the S&P-500 index. *Journal of Empirical Finance* 11:483–507.

Chen, L., M. Pelger, and J. Zhu. 2024. Deep learning in asset pricing. *Management Science* 70:714–750.

Chen, Y., B. T. Kelly, and D. Xiu. 2022b. Expected returns and large language models. *Available at SSRN 4416687* .

Choi, N., and R. W. Sias. 2009. Institutional industry herding. *Journal of financial economics* 94:469–491.

Chou, P.-H., K.-C. Ko, and N.-T. Yang. 2019. Asset growth, style investing, and momentum. *Journal of Banking & Finance* 98:108–124.

Clarke, C., and M. Linn. 2022. Characteristics and the Cross-Section of Covariances. *Available at SSRN* .

Cochrane, J. H. 2011. Presidential address: Discount rates. *The Journal of finance* 66:1047–1108.

Cohen, L., and A. Frazzini. 2008. Economic links and predictable returns. *The Journal of Finance* 63:1977–2011.

Cong, L. W., K. Tang, J. Wang, and Y. Zhang. 2020. AlphaPortfolio for investment and economically interpretable AI. *SSRN, https://papers. ssrn. com/sol3/papers. cfm* .

Cremers, K. M., and V. B. Nair. 2005. Governance mechanisms and equity prices. *the Journal of Finance* 60:2859–2894.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under-and overreactions. *the Journal of Finance* 53:1839–1885.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Positive feedback investment strategies and destabilizing rational speculation. *the Journal of Finance* 45:379–395.

DeVault, L., R. Sias, and L. Starks. 2019. Sentiment metrics and investor demand. *The Journal of Finance* 74:985–1024.

Didisheim, A., S. Ke, B. T. Kelly, and S. Malamud. 2023. Complexity in Factor Pricing Models. *Swiss Finance Institute Research Paper* .

Duffie, D. 2010. Presidential address: Asset price dynamics with slow-moving capital. *The Journal of finance* 65:1237–1267.

Easley, D., S. Hvidkjaer, and M. O'hara. 2002. Is information risk a determinant of asset returns? *The journal of finance* 57:2185–2221.

Edelen, R. M., O. S. Ince, and G. B. Kadlec. 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics* 119:472–488.

Ehsani, S., and J. T. Linnainmaa. 2022. Factor momentum and the momentum factor. *The Journal of Finance* 77:1877–1919.

Fama, E. F., and K. R. French. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance* 51:55–84.

Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of financial economics* 116:1–22.

Fan, M., Y. Li, M. Liao, and J. Liu. 2022. A reexamination of factor momentum: How strong is it? *Financial Review* 57:585–615.

Frankel, R., and C. M. Lee. 1998. Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and economics* 25:283–319.

Frijns, B., A. Gilbert, and R. C. Zwinkels. 2016. On the style-based feedback trading of mutual fund managers. *Journal of Financial and Quantitative Analysis* 51:771–800.

Froot, K., and M. Teo. 2008. Style investing and institutional investors. *Journal of Financial and Quantitative Analysis* 43:883–906.

Gabaix, X., R. S. Koijen, R. Richmond, and M. Yogo. 2023. Asset embeddings. *Available at SSRN 4507511* .

Giannone, D., M. Lenza, and G. E. Primiceri. 2021. Economic predictions with big data: The illusion of sparsity. *Econometrica* 89:2409–2437.

Goetzmann, W. N., D. Kim, and R. J. Shiller. 2022. Crash narratives. Tech. rep., National Bureau of Economic Research.

Gompers, P., J. Ishii, and A. Metrick. 2003. Corporate governance and equity prices. *The quarterly journal of economics* 118:107–156.

Green, J., J. R. Hand, and X. F. Zhang. 2013. The supraview of return predictive signals. *Review of Accounting Studies* 18:692–730.

Green, J., J. R. Hand, and X. F. Zhang. 2017. The characteristics that provide independent information about average US monthly stock returns. *The Review of Financial Studies* 30:4389–4436.

Green, T. C., and B.-H. Hwang. 2009. Price-based return comovement. *Journal of Financial Economics* 93:37–50.

Greenwood, R. 2008. Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights. *The review of financial studies* 21:1153–1186.

Griffin, J. M., J. H. Harris, T. Shu, and S. Topaloglu. 2011. Who drove and burst the tech bubble? *The Journal of Finance* 66:1251–1290.

Gu, S., B. Kelly, and D. Xiu. 2020. Empirical asset pricing via machine learning. *The Review of Financial Studies* 33:2223–2273.

Gupta, T., and B. Kelly. 2019. Factor momentum everywhere. *The Journal of Portfolio Management* 45:13–36.

Hameed, A., and J. Xie. 2019. Preference for dividends and return comovement. *Journal of Financial Economics* 132:103–125.

Harvey, C. R., Y. Liu, and H. Zhu. 2016. ... and the cross-section of expected returns. *The Review of Financial Studies* 29:5–68.

Hastie, T., R. Tibshirani, J. H. Friedman, and J. H. Friedman. 2009. *The elements of statistical learning: data mining, inference, and prediction*, vol. 2. Springer.

Hirshleifer, D., D. Mai, and K. Pukthuanthong. 2025a. War discourse and disaster premium: 160 years of evidence from the stock market. *The Review of Financial Studies* 38:457–506.

Hirshleifer, D., D. Mai, and K. Pukthuanthong. 2025b. War Discourse and the Cross Section of Expected Stock Returns. *The Journal of Finance* 80:3589–3637.

Hong, H., and J. C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance* 54:2143–2184.

Hou, K., C. Xue, and L. Zhang. 2020. Replicating anomalies. *The Review of financial studies* 33:2019–2133.

Huang, X. 2019. Mark Twain's Cat: Investment experience, categorical thinking, and stock selection. *Journal of Financial Economics* 131:404–432.

Invesco. 2024. Invesco Global Systematic Investing Study 2024. Tech. rep., Invesco.

Jame, R., and Q. Tong. 2014. Industry-based style investing. *Journal of Financial Markets* 19:110–130.

Jensen, T. I., B. Kelly, and L. H. Pedersen. 2023. Is there a replication crisis in finance? *The Journal of Finance* 78:2465–2518.

Jha, M., J. Qian, M. Weber, and B. Yang. 2024. ChatGPT and corporate policies. Tech. rep., National Bureau of Economic Research.

Kelly, B., S. Malamud, and K. Zhou. 2024. The virtue of complexity in return prediction. *The Journal of Finance* 79:459–503.

Khandani, A. E., and A. W. Lo. 2011. What happened to the quants in August 2007? Evidence from factors and transactions data. *Journal of Financial Markets* 14:1–46.

Kim, A., M. Muhn, and V. Nikolaev. 2023. From transcripts to insights: Uncovering corporate risks using generative ai. *arXiv preprint arXiv:2310.17721* .

Kim, A., M. Muhn, and V. Nikolaev. 2024. Financial statement analysis with large language models. *arXiv preprint arXiv:2407.17866* .

Kozak, S. 2020. Kernel trick for the cross-section. *Available at SSRN 3307895* .

Kozak, S., S. Nagel, and S. Santosh. 2018. Interpreting factor models. *The Journal of Finance* 73:1183–1223.

Kozak, S., S. Nagel, and S. Santosh. 2020. Shrinking the cross-section. *Journal of Financial Economics* 135:271–292.

Kumar, A. 2009. Dynamic style preferences of individual investors and stock returns. *Journal of Financial and Quantitative Analysis* 44:607–640.

Lee, H., X. Lou, G. Ozik, and R. Sadka. 2024. Narrative Momentum. *Available at SSRN 4912496* .

Lehmann, B. N. 1990. Fads, martingales, and market efficiency. *The Quarterly Journal of Economics* 105:1–28.

Leippold, M., and H. Yang. 2021. The anatomy of factor momentum. *Available at SSRN 3517888* .

Lewellen, J. 2002. Momentum and autocorrelation in stock returns. *The Review of Financial Studies* 15:533–564.

Lo, A. W., and A. C. MacKinlay. 1990. When are contrarian profits due to stock market overreaction? *The review of financial studies* 3:175–205.

Lou, D. 2012. A flow-based explanation for return predictability. *The Review of Financial Studies* 25:3457–3489.

McLean, R. D., and J. Pontiff. 2016. Does academic research destroy stock return predictability? *The Journal of Finance* 71:5–32.

Miller, B. P. 2010. The effects of reporting complexity on small and large investor trading. *The Accounting Review* 85:2107–2143.

Mullainathan, S. 2002. Thinking through categories. *Working Paper* .

Muravyev, D., N. D. Pearson, and J. M. Pollet. 2025. Anomalies and their short-sale costs. *The Journal of Finance* 80:3639–3694.

Nagel, S. 2005. Short sales, institutional investors and the cross-section of stock returns. *Journal of financial economics* 78:277–309.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 55:703–708.

Pavlova, A., and T. Sikorskaya. 2023. Benchmarking intensity. *The Review of Financial Studies* 36:859–903.

Peng, L., and W. Xiong. 2006. Investor attention, overconfidence and category learning. *Journal*

of Financial Economics 80:563–602.

Schauten, M. B., R. Willemstein, and R. C. Zwinkels. 2015. A tale of feedback trading by hedge funds. *Journal of Empirical Finance* 34:239–259.

Shleifer, A., and R. W. Vishny. 1997. The limits of arbitrage. *The Journal of finance* 52:35–55.

Teo, M., and S.-J. Woo. 2004. Style effects in the cross-section of stock returns. *Journal of Financial Economics* 74:367–398.

Wahal, S., and M. D. Yavuz. 2013. Style investing, comovement and return predictability. *Journal of Financial Economics* 107:136–154.

Wermers, R. 2012. Matter of style: The causes and consequences of style drift in institutional portfolios. *Available at SSRN 2024259* .

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: journal of the Econometric Society* pp. 817–838.

Yan, X., and L. Zheng. 2017. Fundamental analysis and the cross-section of stock returns: A data-mining approach. *The Review of Financial Studies* 30:1382–1423.

You, H., and X.-j. Zhang. 2009. Financial reporting complexity and investor underreaction to 10-K information. *Review of Accounting studies* 14:559–586.

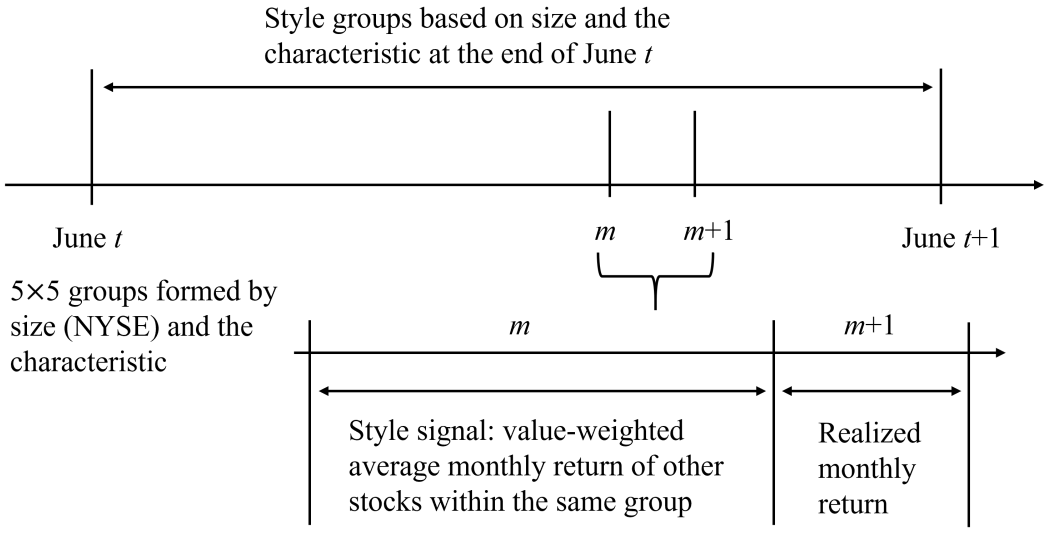


Figure 1: Timeline for signal construction and predictability tests

This figure illustrates the timeline for constructing style signals and testing their ability to predict future stock returns. At the end of each June, style groups are defined by sorting stocks into 5×5 portfolios based on market capitalization (NYSE breakpoints) and one of the 312 characteristics. The resulting style groups are fixed for the following 12 months. For each characteristic, the focal firm's style signal is calculated as the value-weighted average monthly return of other stocks in the same style group. Then, the style signals are used as predictors in forecasting one-month-ahead stock returns.

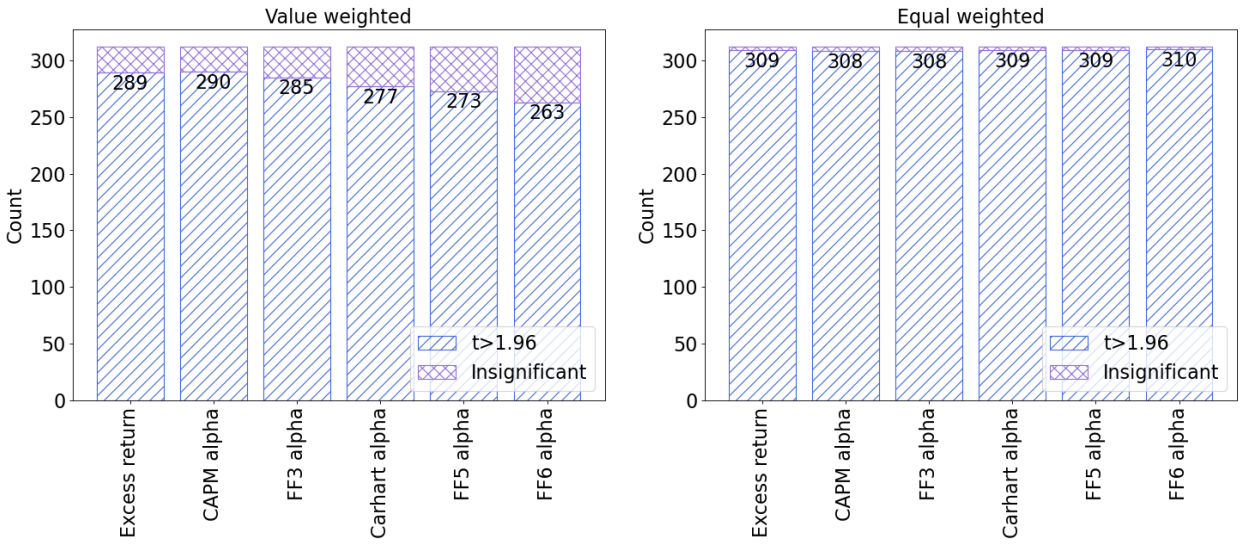


Figure 2: Summary of style strategy performance

This figure reports the number of style strategies with significant mean returns ($t > 1.96$) and insignificant returns. For each style signal, we form decile portfolios each month with a one-month holding period and calculate value- and equal-weighted returns. The style strategy buys stocks in the top decile and sells stocks in the bottom decile. We calculate the average strategy return (Excess return) as well as factor-adjusted returns using CAPM, the three-factor model (FF3) of Fama and French (1996), the Carhart (1997) model, the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6). The t-statistics are calculated based on Newey and West (1987) adjusted standard errors. The sample period is from July 1963 to December 2021.

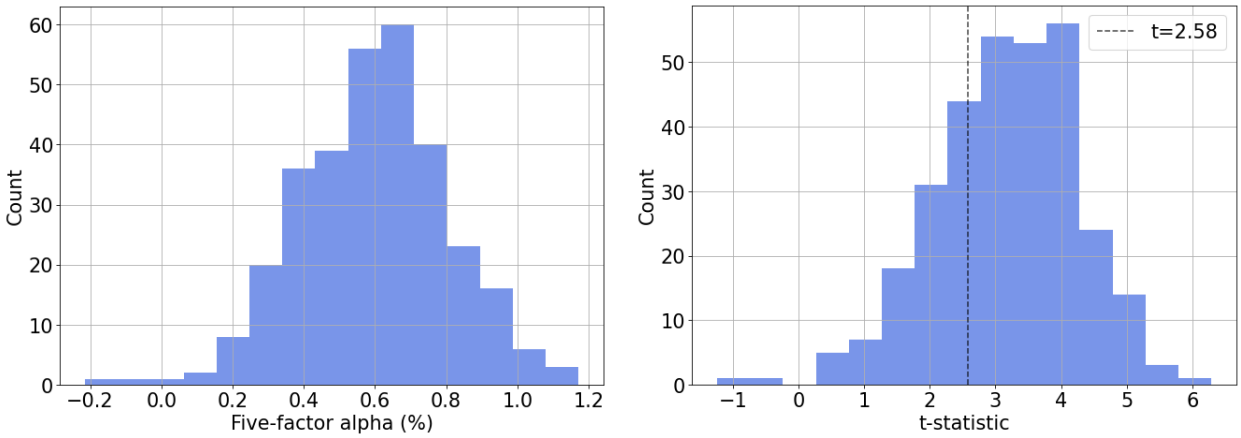


Figure 3: Performance distribution of style strategies

This figure shows the distributions of returns (left) and t-statistics (right) of the 312 style strategies. Returns are adjusted using the five-factor model of Fama and French (2015), and the t-statistics are calculated based on Newey and West (1987) adjusted standard errors. The sample period is from July 1963 to December 2021.

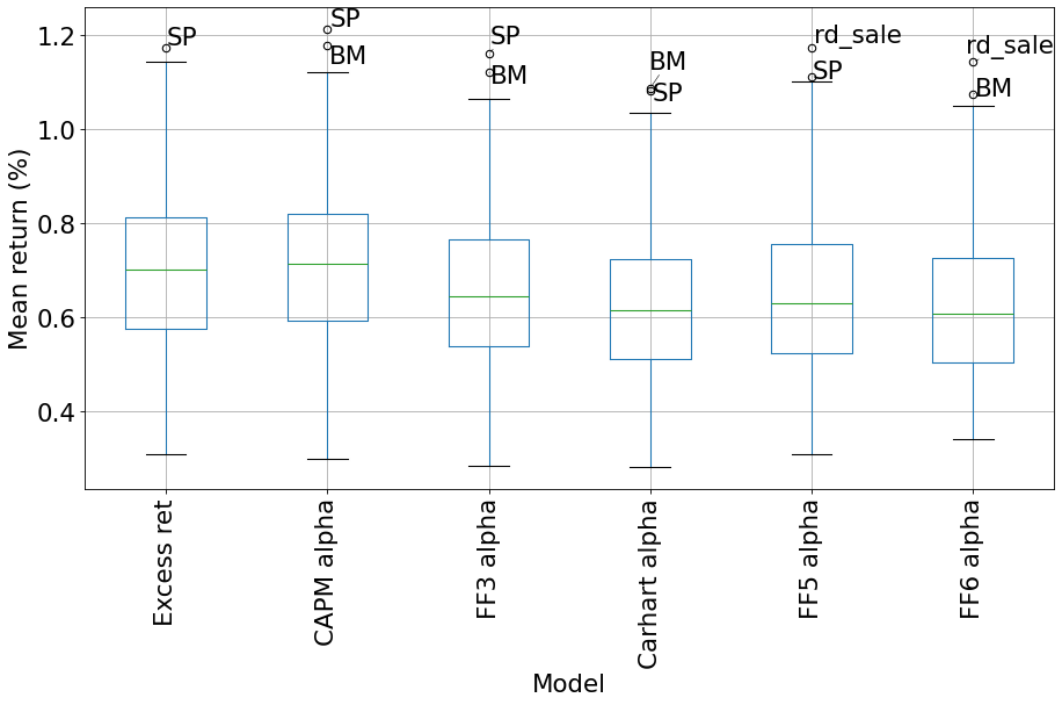


Figure 4: Style portfolio performance by asset pricing models

This figure shows the performance of style strategies across benchmark models. The sample is restricted to strategies with significant average returns. The middle line is the median, and the boxes represent the 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. We calculate the average strategy return (Excess return) as well as factor-adjusted returns using CAPM, the three-factor model (FF3) of Fama and French (1996), the Carhart (1997) model, the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6). The sample period is from July 1963 to December 2021. Variables marked in the figure represent the sales-to-price ratio (SP), the book-to-market ratio (BM), and the R&D-to-sales ratio (rd_sale).

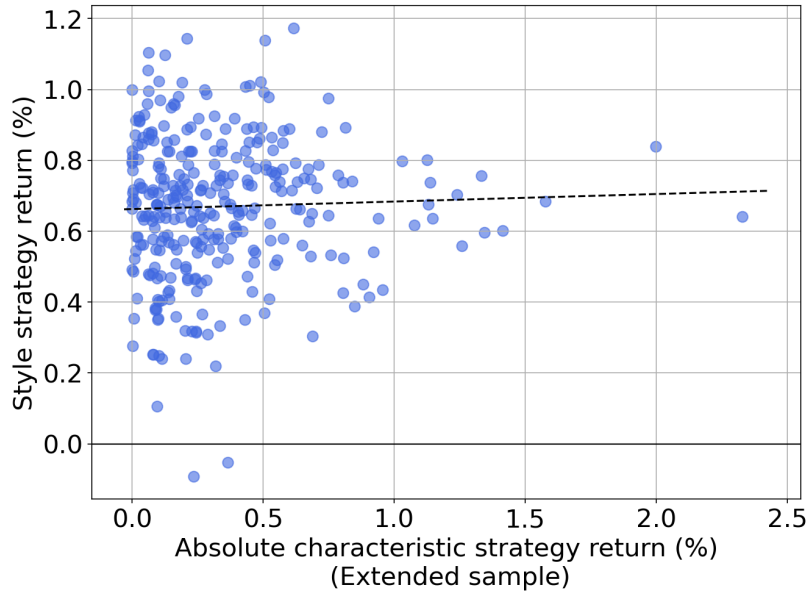




Figure 5: Mean returns of style-based and characteristic-based strategies

This figure presents the scatter plots of style-based strategies (SS) and characteristic-based strategies (CS). The left panel includes all 312 characteristics, and the absolute CS returns are calculated based on value-weighted portfolios from July 1963 to December 2021. In the right panel, the sample is restricted to 150 characteristics with mean CS returns reported by the original studies.

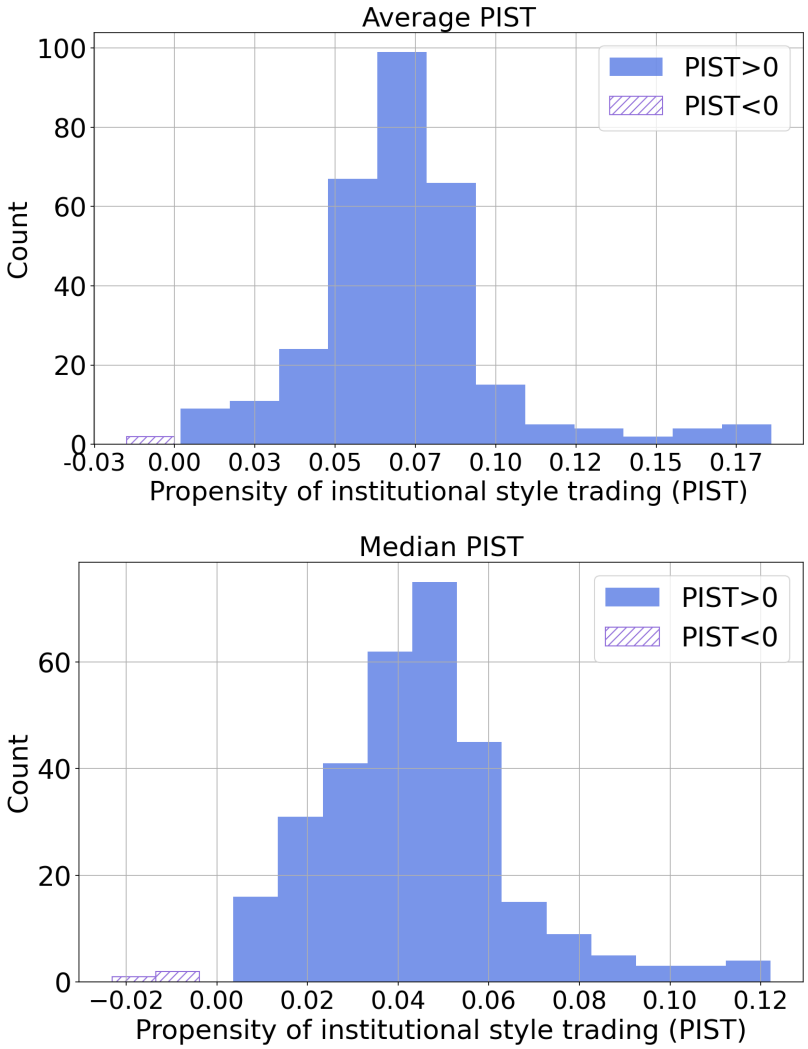


Figure 6: Distributions of estimated PIST

This figure reports the distributions of the propensity of institutional style trading (PIST). PIST is estimated using equation (2). For each style, we calculate the average and median PIST (multiplied by 100) and report the distributions of PIST for the 312 styles.

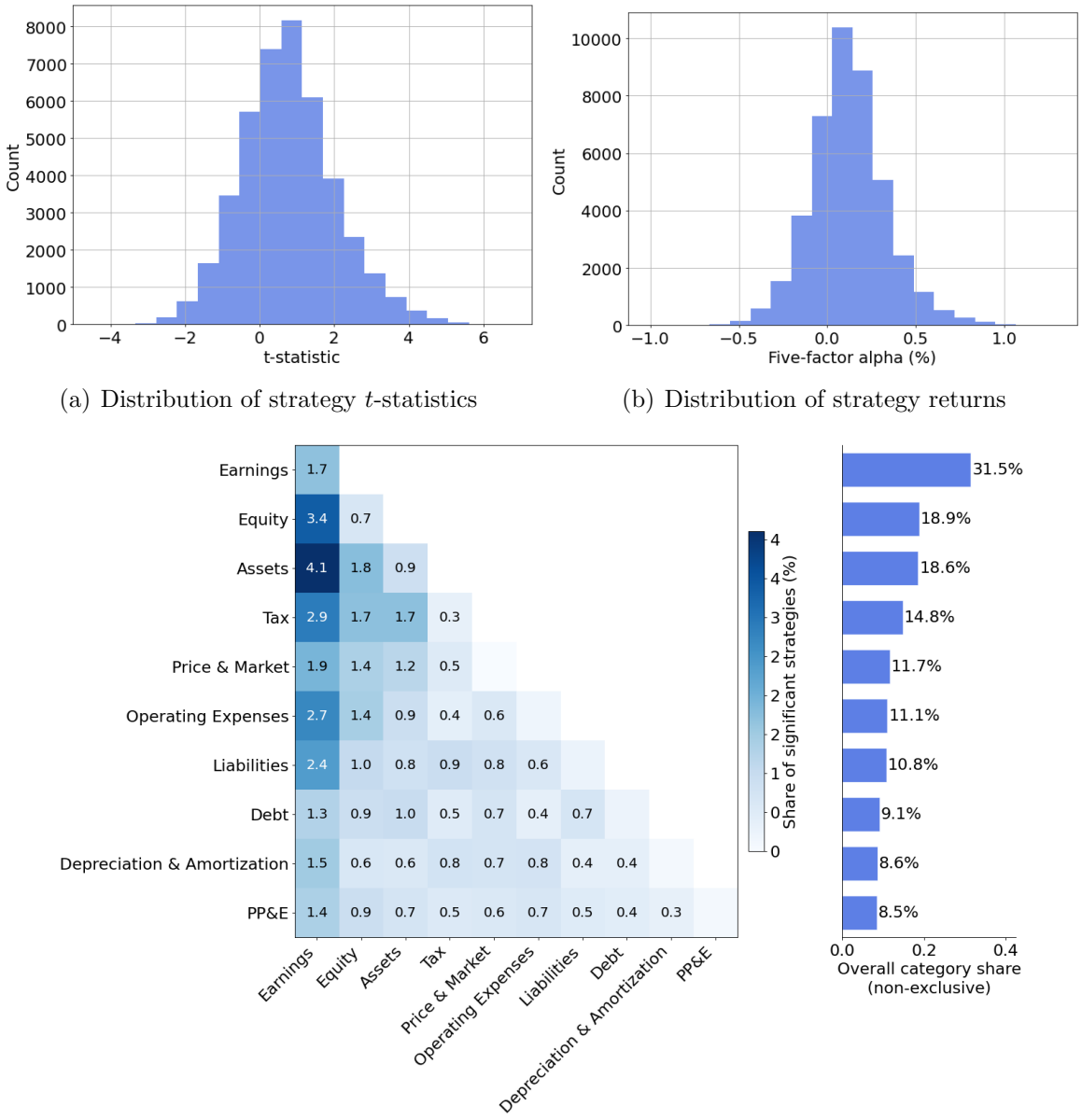
```
Please disregard any previous instructions and consider the following content
    independently.

[Attachment]
The attached .csv file contains a series of financial characteristics, including
    their acronyms (in the "Acronym" column), names (in the "LongDescription"
    column), and detailed definitions (in the "Detailed Definition" column).

[Task]
Please evaluate the complexity of each financial characteristic in designating
    trading strategies by:
1. Assigning a complexity score from 1 to 3, where:
-- 1 indicates "straightforward or easy to compute"
-- 3 indicates "highly complex or intricate "
2. Providing a confidence level for your evaluation, expressed as a value
    between 0 and 1.

[Response Requirement]
1. Base your evaluation on the detailed definitions provided in the attached
    file and consider factors such as calculation complexity, data requirements,
    and conceptual difficulty when assigning scores.
2. Distribute the complexity scores across the 1-3 range, ensuring a maximum of
    150 characteristics share any given score.
3. Return a JSON file in the following format:
{
       "rank": {
              "Acronym 1": "score1"
              "Acronym 2": "score2"
              ...
       },
       "confidence": {
              "Acronym 1": "confidence1"
              "Acronym 2": "confidence2"
              ...
       }
}
```

Figure 7: Prompt to ChatGPT for evaluating complexity of characteristics
This figure presents the detailed prompt used to instruct ChatGPT in assessing the implementation complexity of firm characteristics. The prompt includes specific response requirements, evaluation criteria, and formatting guidelines to ensure consistent complexity scoring across all characteristics. The analysis was conducted using OpenAI's ChatGPT-4o model, accessed in October 2024.



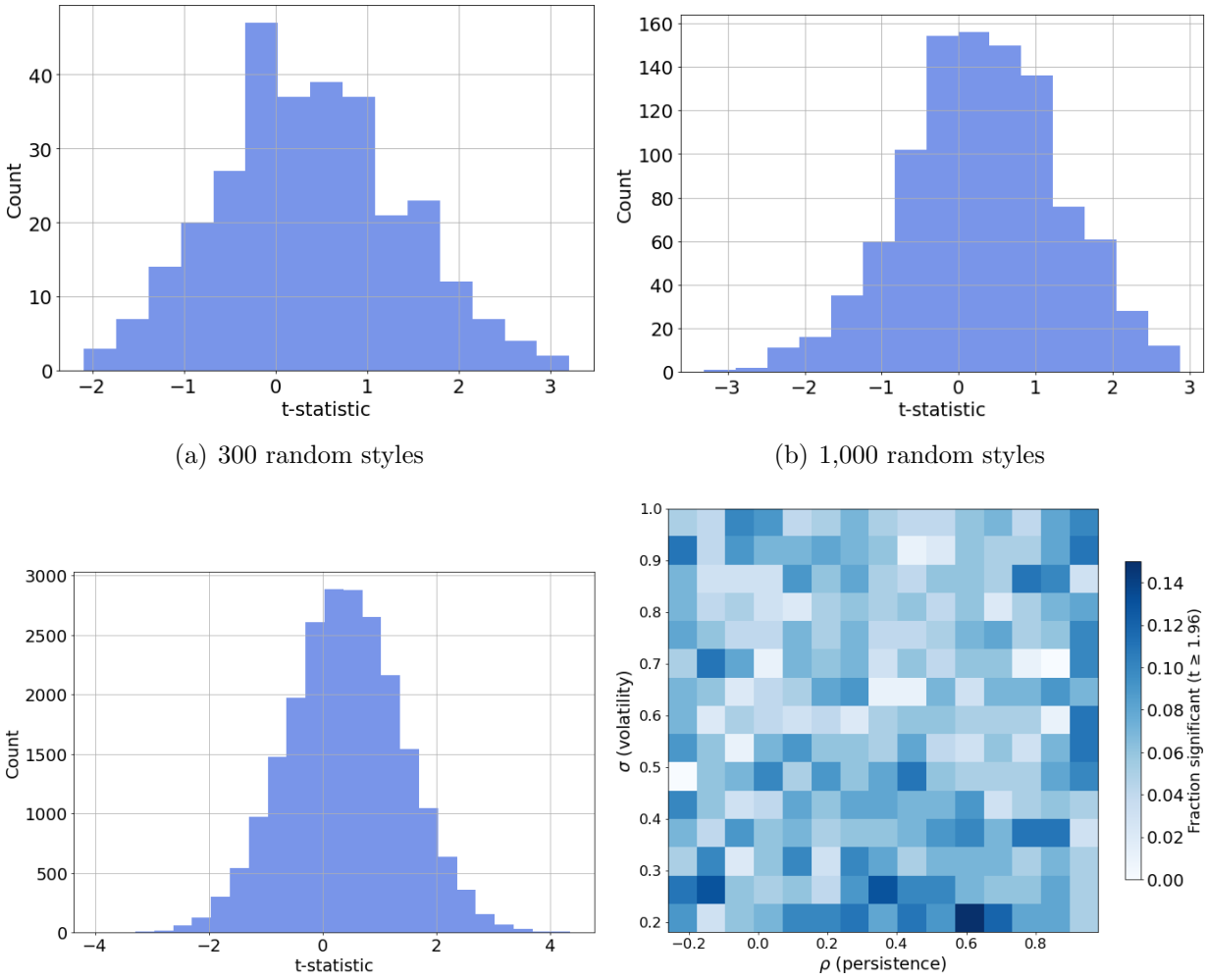
(a) Distribution of strategy t-statistics

(b) Distribution of strategy returns

(c) Category decomposition of significant strategies

Figure 8: Style strategies constructed from Compustat accounting ratios

This figure presents the performance of style strategies constructed from pairwise ratios and changes in ratios of annual Compustat accounting items. Panels (a) and (b) report the distributions of strategy t-statistics and abnormal returns, respectively, for the full set of 42,334 ratio-based strategies. Panel (c) decomposes the contribution of the 10 most prominent accounting categories to significant strategies. The heatmap in Panel (c) displays the fraction of all significant strategies in which one item belongs to category i and the other to category j; each cell represents a mutually exclusive category pair. The adjoining bar chart reports the overall share of significant strategies involving each category (non-exclusive, as each strategy spans two categories). Strategy returns are adjusted using the Fama and French (2015) five-factor model, and the t-statistics are calculated based on Newey and West (1987) adjusted standard errors. The sample period is from July 1963 to December 2021.



(a) 300 random styles

(b) 1,000 random styles

(c) 22,500 style-rounds from pseudo-characteristics

(d) Significance rate across (ρ, σ)

Figure 9: Performance distribution of random style strategies

This figure shows the performance of random style strategies. In Panels (a) and (b), style groups are formed by sorting stocks on randomly assigned numbers, with 300 and 1,000 independent draws, respectively. In Panels (c) and (d), style groups are generated using pseudo-characteristics that follow the AR(1) process defined in equation (9), with parameters calibrated to the empirical distribution of the 312 real characteristics. Panels (a), (b), and (c) present the distribution of strategy t-statistics. Panel (d) displays the fraction of 100 simulation rounds yielding a significant strategy ($t \geq 1.96$) for each point on the (ρ, σ) grid. Strategy returns are adjusted using the Fama and French (2015) five-factor model, and the t-statistics are calculated based on Newey and West (1987) adjusted standard errors. The sample period is from July 1963 to December 2021.

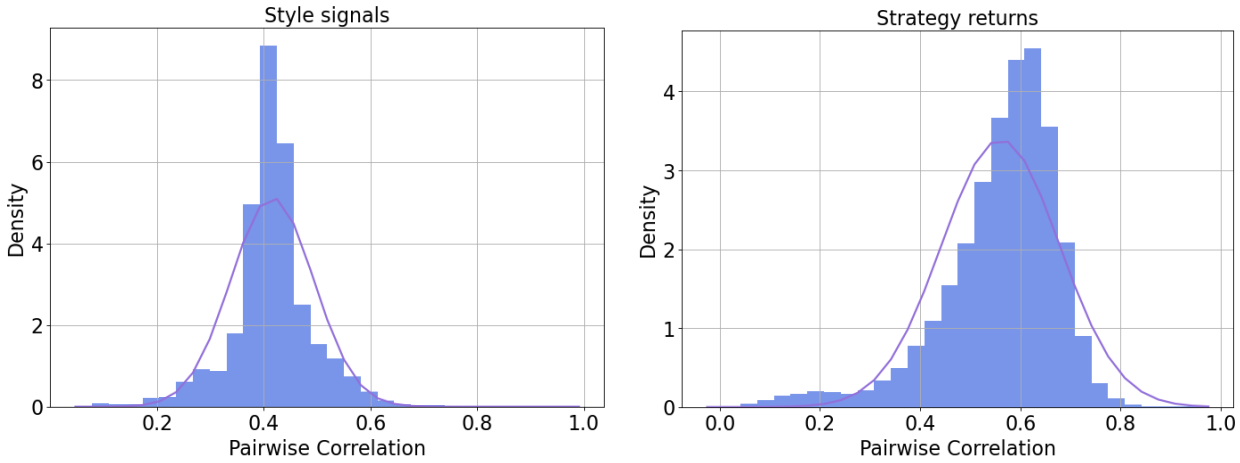


Figure 10: Correlations between styles

This figure reports the distributions of pairwise correlations between style signals (left) and between style strategy returns (right). For stock-level style signals, we compute pairwise cross-sectional correlations each month and then take the time-series averages. For long-short style strategies, we calculate pairwise correlations of monthly strategy returns. The sample period is from July 1963 to December 2021.

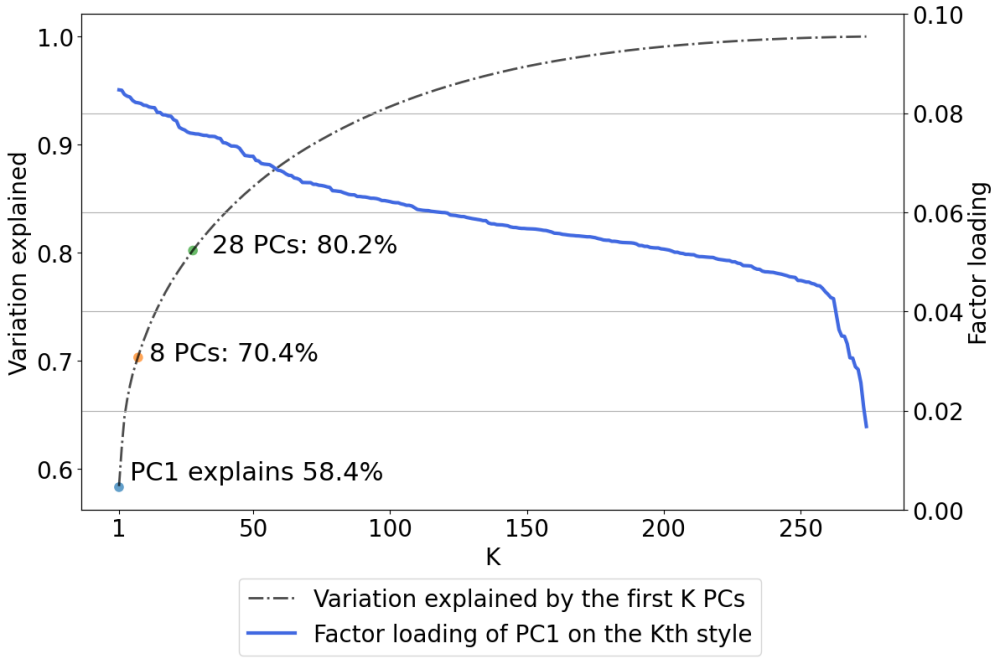


Figure 11: PCA of style strategies

This figure presents the result of the principal component analysis of the style strategies. The dash-dotted line is the cumulative ratio of the total variation of style strategies explained by the first K PCs. The solid line represents the factor loadings of the first PC on style strategies. The sample period is from July 1980 to December 2021.

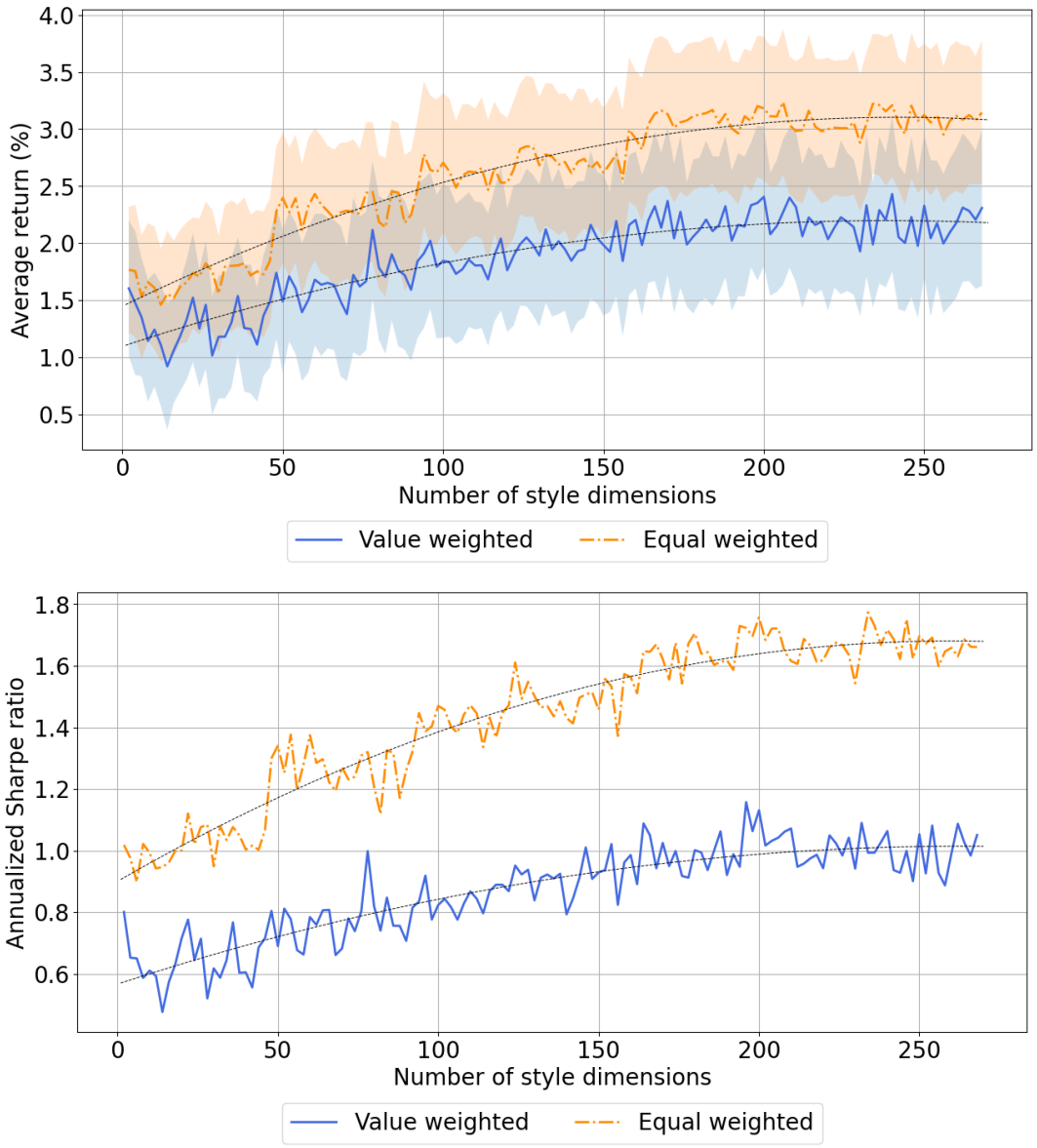


Figure 12: Style dimension and return predictability

This figure plots the performance of style strategies as a function of the number of style dimensions. Each June, stocks are clustered into 50 groups based on d styles by k-means clustering. The style signal is the value-weighted average monthly return of other stocks in the same group. We form decile portfolios each month and calculate value- and equal-weighted returns to the long-short strategy. The figure shows the relationships between d, average returns, and annualized Sharpe ratios. The shaded areas in the upper panel represent the 95% confidence intervals. The sample period is from July 1980 to December 2021.

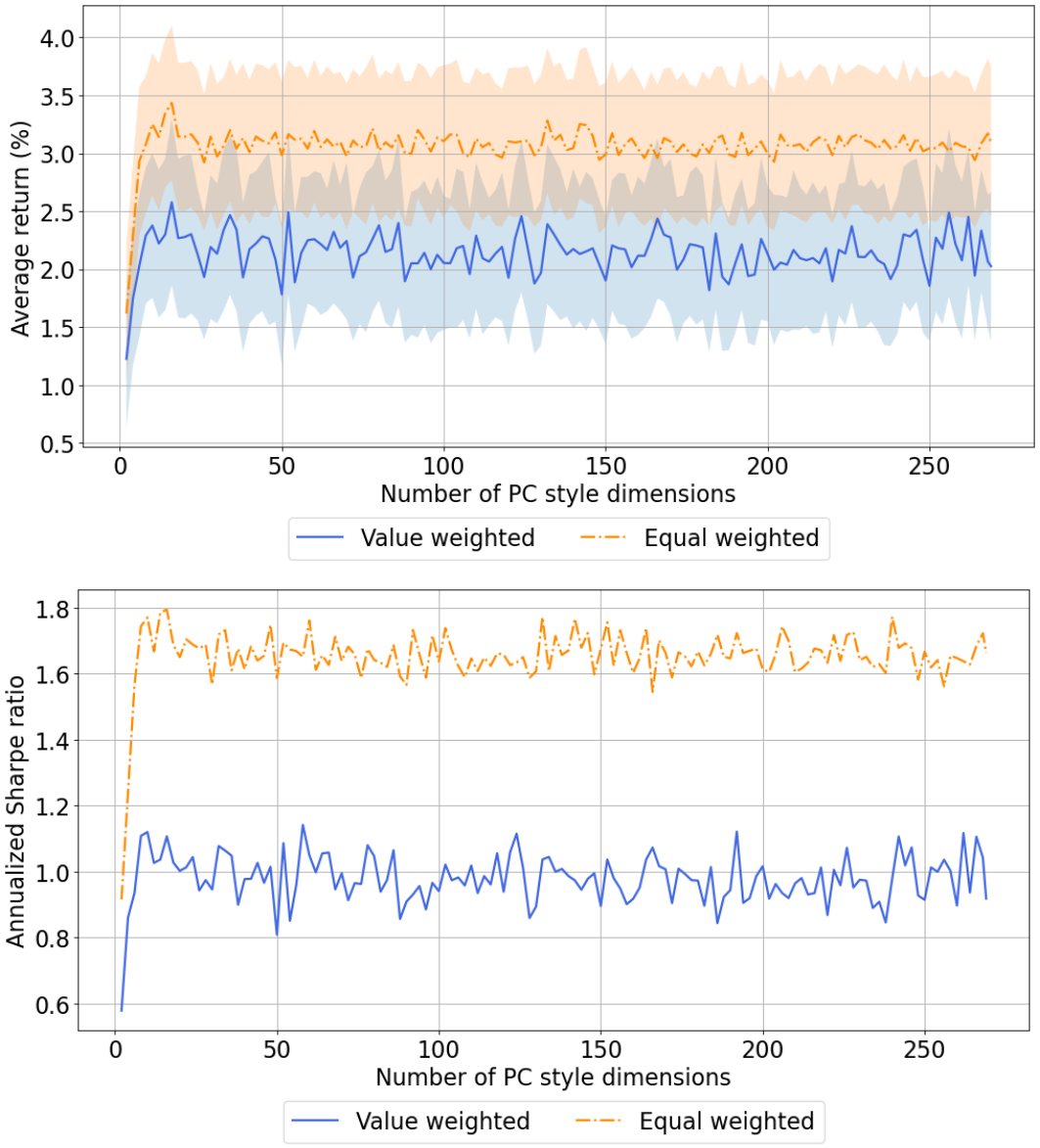


Figure 13: PC styles and return predictability

This figure plots the performance of style strategies as a function of the number of PC style dimensions. Each June, we calculate the principal components (PCs) of characteristics and then categorize stocks into 50 groups based on the first d PCs, using k-means clustering. The style signal is the value-weighted average monthly return of other stocks in the same PC style group. We form decile portfolios each month and calculate value- and equal-weighted returns to the long-short strategy. The figure shows the relationships between d, average returns, and annualized Sharpe ratios. The shaded areas in the upper panel represent the 95% confidence intervals. The sample period is from July 1980 to December 2021.

Table 1: Summary of style strategy performance

This table reports the summary statistics for style strategies. In Panel A and Panel B, strategies are restricted to those with mean returns that are significant at the 5% level; Panel C includes all 312 style strategies. For each style variable, we form decile portfolios based on the style signal each month and calculate value-weighted average returns in the next month. A style strategy is a hedge portfolio that buys stocks in the top decile and sells stocks in the bottom decile. We report the average excess return (Excess return) and factor-adjusted returns using CAPM, the three-factor model (FF3) of Fama and French (1996), the Carhart (1997) model, the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6). The t-statistics are calculated based on Newey and West (1987) adjusted standard errors. The sample period is from July 1963 to December 2021.

	Excess return	CAPM alpha	FF3 alpha	Carhart alpha	FF5 alpha	FF6 alpha
Panel A. Average return (%)						
Mean	0.699	0.713	0.655	0.626	0.643	0.624
Std.Dev.	0.171	0.176	0.168	0.158	0.169	0.162
Min	0.309	0.299	0.285	0.283	0.310	0.342
Median	0.703	0.715	0.646	0.615	0.631	0.607
Max	1.173	1.213	1.160	1.087	1.172	1.143
N	289	290	285	277	273	263
Panel B. t-statistic						
Mean	3.830	3.881	3.805	3.476	3.445	3.308
Median	3.840	3.961	3.843	3.424	3.416	3.289
Std.Dev.	0.964	0.986	0.980	0.862	0.846	0.800
Proportion ($t \geq 3$)	0.761	0.769	0.765	0.682	0.681	0.608
Proportion ($t \geq 2.58$)	0.882	0.879	0.863	0.816	0.806	0.802
N	289	290	285	277	273	263
Panel C. All styles						
Mean average return (%)	0.670	0.684	0.623	0.586	0.594	0.567
Median average return (%)	0.681	0.700	0.634	0.595	0.606	0.573
Mean t-stat	3.644	3.695	3.588	3.234	3.173	3.000
Median t-stat	3.770	3.821	3.705	3.281	3.259	3.041
N	312	312	312	312	312	312

Table 2: The t-statistics of style-based and characteristic-based strategies

This table reports the summary of t-statistics of style-based strategies (SS) conditional on the performance of characteristic-based strategies (CS). In Panel A, CS returns are calculated based on value-weighted portfolios with a one-month holding period from July 1963 to December 2021, with t-statistics calculated based on Newey and West (1987) adjusted standard errors. In Panel B, the t-statistics of CS are obtained from the original studies. We report the average excess return (Excess return) and factor-adjusted returns using CAPM, the three-factor model (FF3) of Fama and French (1996), the Carhart (1997) model, the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6).

	Excess return	CAPM alpha	FF3 alpha	Carhart alpha	FF5 alpha	FF6 alpha
Panel A. Conditional on extended-sample CS performance						
Prop. $t_{SS} \geq 1.96$ and $\lvert t_{CS}\rvert \geq 1.96$	0.975	0.969	0.956	0.939	0.898	0.868
# $\lvert t_{CS}\rvert \geq 1.96$	118	159	159	131	137	114
Prop. $t_{SS} \geq 1.96$ and $\lvert t_{CS}\rvert < 1.96$	0.897	0.882	0.869	0.851	0.857	0.828
# $\lvert t_{CS}\rvert < 1.96$	194	153	153	181	175	198
Prop. $t_{SS} \geq 2.58$ and $\lvert t_{CS}\rvert \geq 2.58$	0.878	0.879	0.816	0.738	0.739	0.625
# $\lvert t_{CS}\rvert \geq 2.58$	74	107	114	84	88	72
Prop. $t_{SS} \geq 2.58$ and $\lvert t_{CS}\rvert < 2.58$	0.794	0.785	0.773	0.719	0.692	0.692
# $\lvert t_{CS}\rvert < 2.58$	238	205	198	228	224	240
Panel B. Conditional on in-sample CS performance						
Prop. $t_{SS} \geq 1.96$ and $\lvert t_{CS}\rvert \geq 1.96$	0.942	0.936	0.931	0.913	0.913	0.873
# $\lvert t_{CS}\rvert \geq 1.96$	173	173	173	173	173	173
Prop. $t_{SS} \geq 1.96$ and $\lvert t_{CS}\rvert < 1.96$	0.920	0.920	0.880	0.840	0.840	0.800
# $\lvert t_{CS}\rvert < 1.96$	25	25	25	25	25	25
Prop. $t_{SS} \geq 2.58$ and $\lvert t_{CS}\rvert \geq 2.58$	0.844	0.850	0.810	0.748	0.728	0.707
# $\lvert t_{CS}\rvert \geq 2.58$	147	147	147	147	147	147
Prop. $t_{SS} \geq 2.58$ and $\lvert t_{CS}\rvert < 2.58$	0.824	0.824	0.824	0.804	0.784	0.765
# $\lvert t_{CS}\rvert < 2.58$	51	51	51	51	51	51

Table 3: Comovement and style strategy returns

This table reports the results from panel regressions of style strategy returns on lagged comovement:

$$R_{style,t+1} = \alpha + \beta Comove_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}.$$

The independent variable $Comove_{style,t}$ is calculated as the correlation coefficient between style signals and the contemporaneous stock returns. $Comove_{style,t}$ is also winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The regression includes time-fixed effects (η_t) and style-fixed effects (γ_{style}). Standard errors are clustered at the month level in columns (1) to (3) and at the style and month levels in columns (4) to (6). The t-statistics are reported in parentheses. The sample period is from July 1963 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Comove	0.104	0.080	0.083	0.104	0.080	0.083
	(3.17)	(2.78)	(2.90)	(3.14)	(2.73)	(2.87)
Time FE	√		√	√		√
Style FE		√	√		√	√
Two-way cluster				√	√	√
N	201060	201060	201060	201060	201060	201060
Adj. R^2	0.56	0.00	0.56	0.56	0.00	0.56

Table 4: Propensity of institutional style trading and style strategy returns

This table reports the results from panel regressions of style strategy returns on the lagged propensity of institutional style trading (PIST):

$$R_{style,t+1} = \alpha + \beta_1 PIST_{style,t} + \beta_2 Comove_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}.$$

The independent variable $PIST_{style,t}$ is calculated from quarterly panel regressions based on equation (2). Regressions also include the style comovement ($Comove_{style,t}$) as the control variable. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The regression includes time-fixed effects (η_t) and style-fixed effects (γ_{style}). Standard errors are clustered at the month level. The t-statistics are reported in parentheses. The sample period is from July 1980 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
PIST	0.050	0.049	0.049	0.051	0.048	0.049
	(2.30)	(2.25)	(2.25)	(2.36)	(2.25)	(2.26)
Comove				0.116	0.096	0.096
				(2.82)	(2.70)	(2.71)
Time FE	√		√	√		√
Style FE		√	√		√	√
N	150759	150759	150759	150759	150759	150759
Adj. R^2	0.54	0.00	0.54	0.54	0.00	0.54

Table 5: Retail investor style trading and style strategy performance

This table reports the results from cross-sectional regressions:

$$\mathbb{E}[R_{style}] = \alpha + \beta_1 \overline{PRST}_{style} + \beta_2 \overline{PIST}_{style} + \beta_3 \overline{Comove}_{style} + \varepsilon_{style}.$$

The dependent variable is the average return of style strategies (Panel A) or the annualized Sharpe ratio of style strategies (Panel B). The main independent variable of interest is the average propensity of retail style trading ($\overline{\text{PRST}}$) of the corresponding style, as calculated using equations (4) and (5). Control variables include the average propensity of institutional style trading ($\overline{\text{PIST}}$) and the average comovement ($\overline{\text{Comove}}$) associated with the style. We also include fixed effects of the economic categories of the underlying characteristics. Data on characteristics' economic categories are obtained from the Open Source Asset Pricing website (Chen and Zimmermann, 2022). For example, the book-to-market ratio (BM) is categorized under the value category, while return-on-assets (ROA) is categorized under profitability. Consequently, styles derived from BM and ROA are classified under their respective economic categories, namely, value and profitability. The t-statistics are calculated based on the White (1980) heteroskedasticity-consistent standard errors and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Style strategy average return						
$\overline{\text{PRST}}$	0.034	0.039	0.039	0.042	0.020	0.027
	(2.42)	(2.74)	(2.95)	(3.08)	(2.05)	(2.72)
$\overline{\text{PIST}}$			0.044	0.040	0.054	0.049
			(3.51)	(3.35)	(5.18)	(4.47)
$\overline{\text{Comove}}$					0.123	0.137
					(10.91)	(11.06)
Econ.Cat FE		√		√		√
N	312	310	312	310	312	310
Adj. R^2	0.03	0.16	0.07	0.19	0.44	0.54
Panel B. Style strategy Sharpe ratio						
$\overline{\text{PRST}}$	0.019	0.029	0.025	0.033	0.014	0.024
	(1.90)	(2.71)	(2.65)	(3.23)	(1.94)	(2.97)
$\overline{\text{PIST}}$			0.048	0.043	0.053	0.048
			(5.01)	(4.63)	(6.59)	(5.73)
$\overline{\text{Comove}}$					0.068	0.079
					(8.67)	(9.04)
Econ.Cat FE		√		√		√
N	312	310	312	310	312	310
Adj. R^2	0.01	0.15	0.12	0.22	0.33	0.44

Table 6: Characteristic attractiveness and style strategy returns

This table reports the results from panel regressions of style strategy returns on the lagged characteristic return spread (CRS):

$$R_{style,t+1} = \alpha + \beta_1 CRS_{style,t} + \beta_2 Comove_{style,t} + \beta_3 PIST_{style,t} + \eta_t + \gamma_{style} + \varepsilon_{style,t+1}.$$

The independent variable $CRS_{style,t}$ is the absolute value of the monthly strategy return of the corresponding characteristic. The characteristic strategy is defined as a high-minus-low hedge strategy, where stocks are sorted into decile portfolios based on the relevant characteristic, and the portfolio returns are value weighted. The regression also includes comovement (Comove) and the propensity of institutional style trading (PIST) as control variables. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The regression includes time-fixed effects (η_t) and style-fixed effects (γ_{style}). Panel B presents results using alternative proxies for characteristic attractiveness, including: (1) returns from characteristic-based strategies; (2) returns from characteristic-based strategies, signed according to the predictive power of the underlying characteristics; (3) the previous month's style strategy return; (4) the absolute value of the lagged style strategy return; (5) the standard deviation of returns for characteristic-based decile portfolios; and (6) the difference in the average style signal values between the top and bottom deciles of the style strategy. Standard errors are clustered at the month level. The t-statistics are reported in parentheses. The sample period is from July 1963 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Characteristic return spread and style returns						
CRS	0.077	0.076	0.077	0.066	0.085	0.072
	(3.47)	(4.55)	(4.71)	(4.61)	(4.28)	(4.21)
Comove				0.074		0.086
				(2.65)		(2.50)
PIST					0.050	0.049
					(2.29)	(2.29)
Time FE	√		√	√		√
Style FE		√	√		√	√
N	200304	200304	200304	200304	150314	150314
Adj. R^2	0.56	0.00	0.56	0.56	0.54	0.55
Panel B. Alternative proxies						
Proxy=	Lagged characteristic strategy return	Lagged and signed characteristic strategy return	Lagged style strategy return	Absolute value of lagged style strategy return	Std.Dev. of lagged portfolio returns across characteristic deciles	Sorting variable spread
CRS	0.077	0.073	0.077	0.073	0.077	0.063
	(3.45)	(3.19)	(3.45)	(3.46)	(5.04)	(3.82)
Proxy	0.007	0.003	0.019	0.033	0.001	0.046
	(0.74)	(0.22)	(0.77)	(1.64)	(0.07)	(1.50)
Time FE	√	√	√	√	√	√
N	200304	147293	200213	200213	200304	200304
Adj. R^2	0.56	0.55	0.56	0.56	0.56	0.56

Table 7: Complexity and style strategy performance

This table reports the results from cross-sectional regressions:

$$\mathbb{E}[R_{style}] = \alpha + \beta Complexity_{style} + Controls + \varepsilon_{style}.$$

The dependent variable is the average return of style strategies. The main independent variable of interest, $Complexity_{style}$, is the average complexity score assigned by ChatGPT based on characteristic descriptions. Panel A reports results with various fixed effect specifications, including economic category (Econ.Cat), data requirement category (Data.Cat), and publication journal (Journal). In Panel B, we consider control variables studied in previous sections, including the average propensity of institutional style trading ($\overline{\text{PIST}}$), the average propensity of retail style trading ($\overline{\text{PRST}}$), the average comovement ($\overline{\text{Comove}}$), and the average characteristic-return spread ($\overline{\text{CRS}}$). Economic category fixed effects are also included in Panel B. All characteristic-related data are sourced from the Open Source Asset Pricing website (Chen and Zimmermann, 2022). The t-statistics are calculated based on the White (1980) heteroskedasticity-consistent standard errors and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Panel A. Baseline result					
Complexity	-0.213	-0.193	-0.205	-0.184	-0.175
	(-5.80)	(-5.18)	(-5.53)	(-4.64)	(-3.79)
Econ.Cat FE		√			√
Data.Cat FE			√		√
Journal FE				√	√
N	312	310	312	302	300
Adj. R^2	0.10	0.20	0.11	0.11	0.19
Panel B. Additional controls					
Complexity	-0.193	-0.184	-0.180	-0.074	-0.178
	(-5.18)	(-4.93)	(-4.83)	(-2.16)	(-4.68)
$\overline{\text{PIST}}$		0.032			
		(2.62)			
$\overline{\text{PRST}}$			0.033		
			(2.43)		
$\overline{\text{Comove}}$				0.129	
				(10.32)	
$\overline{\text{CRS}}$					0.029
					(1.99)
Econ.Cat FE	√	√	√	√	√
N	310	310	310	310	310
Adj. R^2	0.20	0.22	0.49	0.22	0.21

Table 8: Characteristic rank distribution across style signal deciles

This table reports the distribution of firm characteristics across style signal-sorted decile portfolios. Each month, for each style, stocks are independently sorted into deciles by the style signal and by the underlying characteristic. We report the average characteristic decile within each style signal group, as well as the proportions of stocks belonging to the bottom and top characteristic deciles. We first take the time-series average for each style and then compute cross-style averages. The sample comprises 275 styles whose underlying characteristics have at least 10 distinct values such that decile sorts are well defined.

Style signal	Average characteristic	Proportion in extreme characteristic decile (%)	
decile	decile	Bottom	Top
1	5.44	10.83	10.26
2	5.43	10.45	9.80
3	5.45	9.46	9.11
4	5.48	9.01	8.94
5	5.50	8.84	8.98
6	5.51	8.89	9.12
7	5.52	9.21	9.53
8	5.52	9.91	10.16
9	5.51	11.40	11.63
10	5.50	12.19	12.20

Table 9: Principal components of style strategies

This table reports the results of the principal component analysis on style strategies. The second column reports the average R^2 from time-series regressions of style strategy returns on the first K PCs; the third column reports the portion of the variation in style strategies explained by the first K PCs. Columns 4 to 7 report the factor loadings, names, descriptions, and categories of 20 styles on the first PC in descending order. The sample period is from July 1980 to December 2021.

K	Time-variation		The first principal component			
	Avg. R^2	Var. Explained	Loading	Style	Description	Category
1	0.576	0.584	0.085	CF	Cash flow to market	valuation
2	0.609	0.620	0.085	IdioVolCAPM	Idiosyncratic risk (CAPM)	risk and volatility
3	0.635	0.648	0.084	BetaFP	Frazzini-Pedersen Beta	risk and volatility
4	0.649	0.664	0.083	IdioVol3F	Idiosyncratic risk (three factor)	risk and volatility
5	0.660	0.677	0.083	rd_sale	R&D to sales	investment alt
6	0.669	0.688	0.083	RoE	net income / book equity	profitability
7	0.677	0.696	0.082	IdioVolQF	Idiosyncratic risk (q factor)	risk and volatility
8	0.685	0.704	0.082	RetNOA_q	Return on Net Operating Assets	composite accounting
9	0.691	0.712	0.082	EquityDuration	Equity Duration	valuation
10	0.698	0.719	0.082	DelEqu	Change in equity to assets	investment

Appendix to "Pervasive Styles"

This appendix provides additional empirical results omitted from the paper for the sake of brevity.

- Figure A1: Style pricing under alternative portfolio specifications
- Figure A2: Style effects with controls for factor momentum
- Figure A3: Within- and cross-industry style pricing
- Figure A4: Style pricing under alternative style constructions and data sources
- Table A1: The role of complexity: comparing styles and characteristics
- Table A2: Summary of residual style strategies

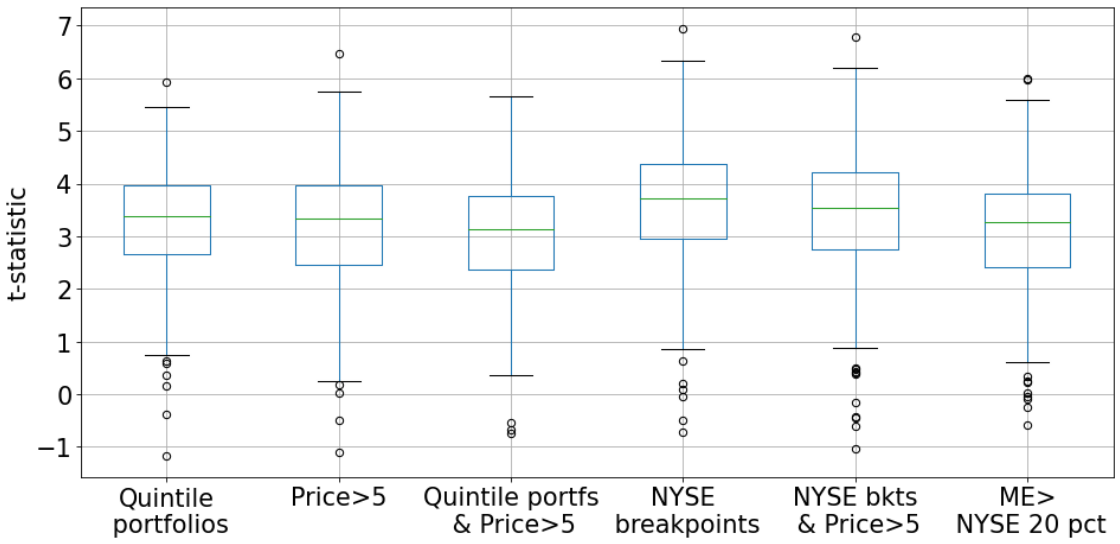


Figure A1: Style pricing under alternative portfolio specifications

This figure plots the t-statistics of 312 style strategies under alternative portfolio specifications. The middle line is the median, and the boxes represent the 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. The t-statistics are based on Newey and West (1987) standard errors, and the sample period is from July 1963 to December 2021.

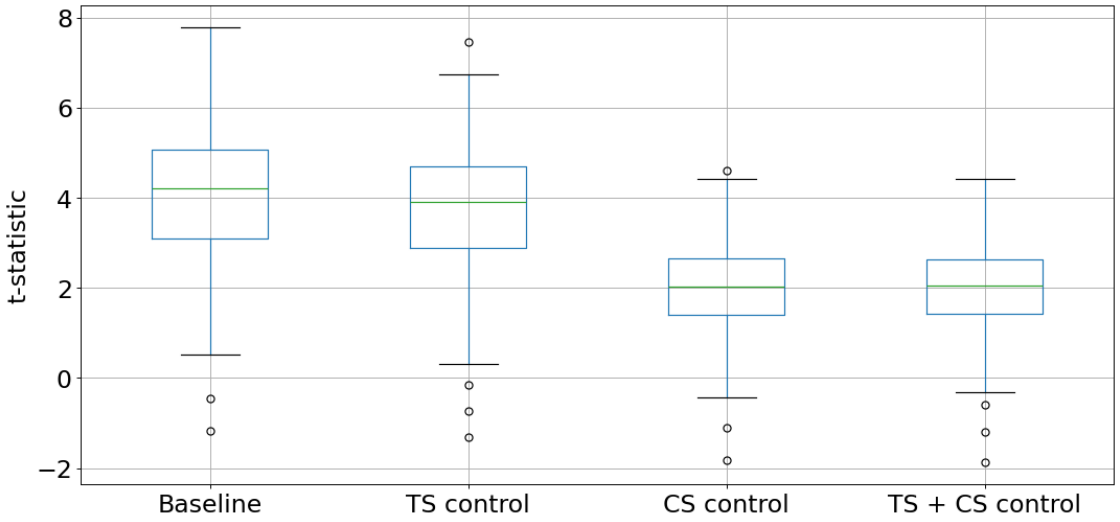


Figure A2: Style effects with controls for factor momentum

This figure shows the t-statistics for the abnormal returns of 312 style strategies. The baseline specification regresses each strategy's monthly return on the Fama and French (2015) five factors, the momentum factor, and the short-term reversal factor. The remaining three specifications progressively add the time-series (TS) factor momentum of Ehsani and Linnainmaa (2022), the cross-sectional (CS) factor momentum of Arnott et al. (2023), or both. The middle line is the median, and the boxes represent the 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. The t-statistics are computed based on Newey and West (1987) standard errors.

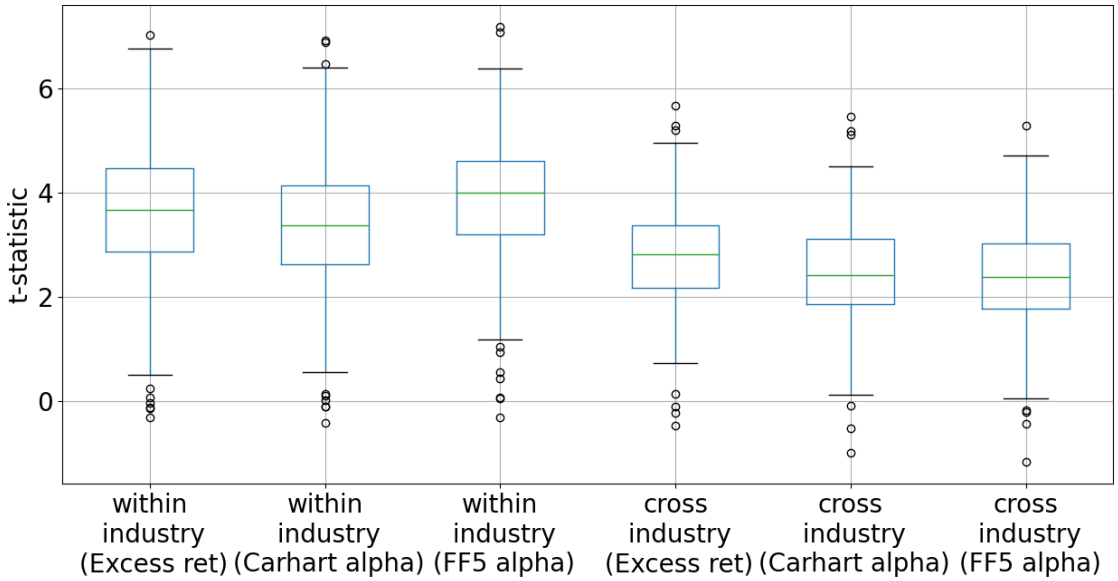


Figure A3: Within- and cross-industry style pricing

This figure plots the t-statistics of 312 style strategies for which the return signals are calculated as the value-weighted average returns of style peers within the same industry or in different industries. Industries are defined based on the four-digit SIC codes. The middle line is the median, and the boxes represent the 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. The t-statistics are based on Newey and West (1987) standard errors, and the sample period is from July 1963 to December 2021.

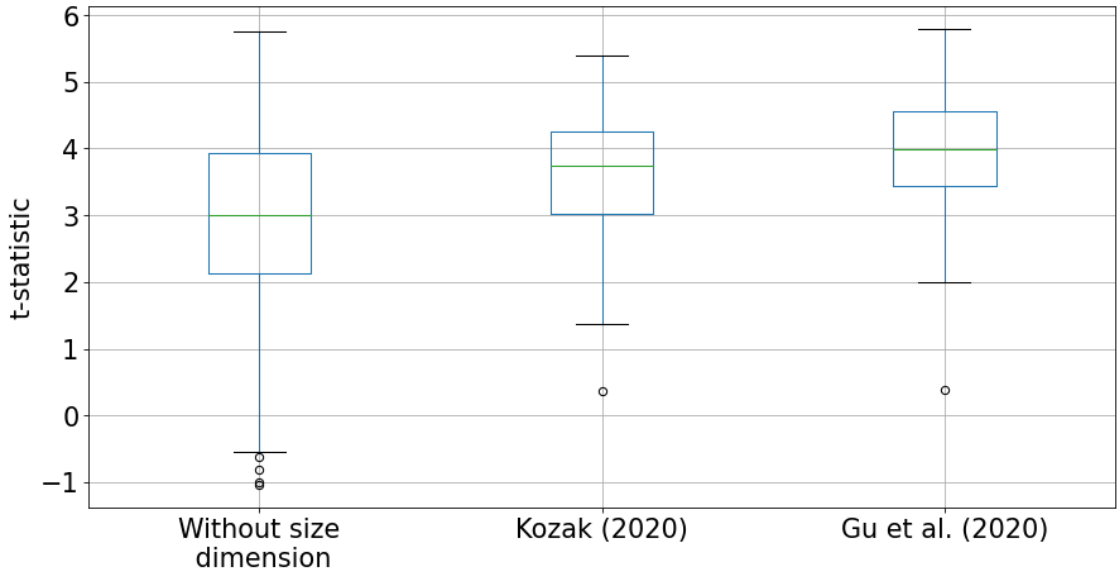


Figure A4: Style pricing under alternative style constructions and data sources This figure plots the t-statistics of style strategies under alternative style constructions and characteristic datasets. The middle line is the median, and the boxes represent the 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. The t-statistics are based on Newey and West (1987) standard errors. The sample period for the Kozak (2020) dataset is from July 1963 to December 2019; the sample period for the Gu et al. (2020) dataset is from July 1963 to December 2021.

Table A1: The role of complexity: comparing styles and characteristics

This table reports the results from cross-sectional regressions:

$$SR_i = \alpha + \beta Complexity_i + Controls + \varepsilon_i$$

The dependent variable is the annualized Sharpe ratio of trading strategies, examined separately for style strategies (Panel A) and characteristic-based strategies (Panel B). The main independent variable of interest is the average complexity score assigned by ChatGPT based on characteristic descriptions ($Complexity_i$), which remains consistent across both panels. For characteristic-based strategies, we employ signed Sharpe ratios by adjusting characteristic returns to ensure positive expected values. In cases where characteristics lack clear return predictability, we utilize the absolute value of average returns when computing the signed Sharpe ratio. We consider several specifications of fixed effects, including economic category (Econ.Cat), data requirement category (Data.Cat), and publication journal (Journal). All characteristic-related data are sourced from the Open Source Asset Pricing website (Chen and Zimmermann, 2022). The t-statistics are calculated based on the White (1980) heteroskedasticity-consistent standard errors and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Panel A. Style strategy performance					
Complexity	-0.133	-0.105	-0.126	-0.113	-0.083
	(-5.24)	(-3.92)	(-4.92)	(-4.05)	(-2.60)
Econ.Cat FE		√			√
Data.Cat FE			√		√
Journal FE				√	√
N	312	310	312	302	300
Adj. R^2	0.07	0.15	0.10	0.08	0.16
Panel B. Placebo test: Characteristic strategy performance					
Complexity	-0.066	-0.058	-0.074	-0.039	-0.004
	(-1.63)	(-1.36)	(-1.86)	(-0.89)	(-0.09)
Econ.Cat FE		√			√
Data.Cat FE			√		√
Journal FE				√	√
N	312	310	312	302	300
Adj. R^2	0.00	0.18	0.11	0.03	0.22

Table A2: Summary of residual style strategies

This table reports the summary statistics of residual style strategies having mean returns that are significant at the 5% level. For each style, the residual signal is the residual from monthly cross-sectional regressions of the style signal on the contemporaneous monthly return of the focal stock. Then, we form value-weighted decile portfolios based on the residual style signal and hold them for one month. A residual style strategy is a hedge portfolio that buys stocks in the top decile and sells stocks in the bottom decile. Panel A reports the mean returns, and Panel B reports the corresponding t-statistics, which are calculated based on Newey and West (1987) adjusted standard errors. We report the average excess return (Excess return) and factor-adjusted returns using CAPM, the three-factor model (FF3) of Fama and French (1996), the Carhart (1997) model, the five-factor model (FF5) of Fama and French (2015), and the momentum-augmented five-factor model (FF6). The sample period is from July 1963 to December 2021.

	Excess return	CAPM alpha	FF3 alpha	Carhart alpha	FF5 alpha	FF6 alpha
Panel A. Average return (%)						
Mean	0.752	0.759	0.689	0.679	0.679	0.667
Std.Dev.	0.175	0.177	0.169	0.165	0.167	0.169
Min	0.348	0.361	0.322	0.305	0.292	0.286
Median	0.758	0.763	0.692	0.668	0.661	0.647
Max	1.238	1.261	1.197	1.162	1.170	1.161
N	294	292	289	288	279	282
Panel B. t-statistic						
Mean	4.099	4.123	4.031	3.799	3.711	3.597
Median	4.220	4.212	4.123	3.823	3.742	3.575
Std.Dev.	1.034	1.042	1.031	0.951	0.903	0.901
Proportion ($t \geq 3$)	0.813	0.822	0.799	0.747	0.767	0.723
Proportion ($t \geq 2.58$)	0.901	0.894	0.896	0.889	0.857	0.851
N	294	292	289	288	279	282