Pervasive Styles *

Huaixin Wang

December 2025

Abstract

The performance of investment styles positively predicts stock returns because of the price pressure from positive feedback trading. This paper provides cross-style examinations by employing a comprehensive set of 312 firm characteristics. I show that over 80% of style-based trading strategies yield significantly positive returns, which holds true even for characteristics without inherent predictive ability. The style pricing effect is stronger under several conditions: (1) increased return comovement; (2) heightened institutional trading; (3) more retail participation; (4) greater style attractiveness; and (5) lower implementation hurdle. Identifying styles in high-dimensional spaces enhances strategy performance, while a sparse model based on principal components of characteristics captures the potential return predictability.

JEL Classification: G11, G12, G23, C55

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

*Preliminary draft, please do not circulate. I am grateful to Jianfeng Yu for his continuous guidance and encouragement. I thank Jingda Yan and seminar participants at the University of Macau FBA for helpful comments. All errors are my own. Author affiliation/contact information: Huaixin Wang is with the Faculty of Business Administration, University of Macau. Email: huaixinwang@um.edu.mo.

1 Introduction

Behavioral finance theory posits that asset labeling plays a pivotal role in driving price dynamics (Mullainathan, 2002; Barberis and Shleifer, 2003). Retail investors exhibit certain habitats due to categorical thinking (Peng and Xiong, 2006; Green and Hwang, 2009) or personal experience (Huang, 2019); Institutions classify assets into "styles" as a way to specialize investment strategies and cater to market attention (Froot and Teo, 2008; Ben-David et al., 2023). Because of coordinated demand, style-level capital allocations induce return comovement beyond what is justified by fundamentals. The price pressure from pursuing style performance generates predictability in asset returns.[1]

Value (e.g., book-to-market) and momentum (e.g., one-year return) stand as the most widely adopted dimensions in academic research for defining investment styles. The existing approach and evidence, however, give rise to several considerations. First, investment strategies are highly 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 typically share correlated fundamentals. It thus becomes challenging, when focusing on a single style or index, to distinguish price pressure from other channels such as underreaction-driven slow information diffusion (Cohen and Frazzini, 2008). Furthermore, 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, I show that return predictability arising from style investing is *pervasive* across a comprehensive set of characteristics.[2] Notably, this style effect emerges even when the underlying characteristic itself lacks predictive power. Second and more important, I investigate what drives the variation in style effect strength. While return predictability is widespread, there exists substantial *heterogeneity* consistent with the price pressure hypothesis. Third, I assess the extent to which these styles can be captured in a parsimonious model, given style-induced trading as their *common* driver. It turns out that

[1]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, 2003; Chen and De Bondt, 2004; Wahal and Yavuz, 2013; Chou et al., 2019; Ben-David et al., 2022, 2024).

[2]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 focuses on exploring the *heterogeneity* and commonality across a large set of styles rather than proposing a composite momentum trading strategy.

high dimensionality is required to capture the documented return predictability. Sparsity is achievable when using principal components of characteristics for style classification. These cross-style examinations enable me to assess the market impact of style investing in a manner that is difficult to approach using only a single characteristic.

Specifically, I 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, I construct stock-level style signals by grouping stocks using size-characteristic sorted portfolios, and computing average returns of peer stocks in the same style category. Then, I sort stocks based on 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, I find that 289 trading strategies, using value-weighted portfolios, generate positive returns significant at the 5% level. Depending on factor adjustments, between 263 and 290 strategies remain significant. This indicates that a minimum of 84% of the style signals demonstrate predictive ability for stock returns.

A well-documented phenomenon in asset pricing is the tendency for anomalies to attenuate over extended sample periods. In my sample, only 118 characteristic-based trading strategies earn significant returns, with this number further declining to 94 after controlling for the q-factors (Hou et al., 2015). 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. In particular, the correlation in average profits between style-based and characteristic-based strategies is near zero. 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 had predictive power or not.

Having established the prevalence of style-based pricing effects, I turn to investigating their key determinants. Theory such as Barberis and Shleifer (2003) suggests 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 me to test several predictions of this mechanism by analyzing cross-style heterogeneity. In my first test, I hypothesize that higher return comovement implies a higher degree of synchronized trading, therefore generating stronger predictability. Consistently, I find that styles associated with greater comovement exhibit higher strategy returns. Style-level panel regression shows 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 my 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.

I measure the propensity of institutional trading (PIT) on styles by regressing changes in institutional ownership on style signals. The results show that a one standard deviation increase in PIT corresponds to an approximate 4.9 bps increase in future style strategy returns, both in cross-section and time series. This positive relationship also distinguishes style investing from the underreaction-driven story. If the return predictability from style grouping reflects the slow dissemination of connected fundamental news (Cohen and Frazzini, 2008), then increased PIT should alleviate mispricing because of the facilitated incorporation of information. However, my findings reveal that institutional trading is associated with amplified anomaly returns. I 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 would like to 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, I show that large characteristic return spreads predict stronger future style returns.

The last factor I examine is the complexity of characteristics. Implementation hurdle significantly influences the adoption of characteristics in style investing and hence their subsequent impact on the stock market. Using OpenAI's ChatGPT, a state-of-the-art large language model, I evaluate the complexity of 312 characteristics based on their detailed textual descriptions. I show that 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.[3]

As I 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, I 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 is in sharp contrast to 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, I 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 I calculate style signals and form long-short portfolios analogously. By examining style strategy performance under different d values, I 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 if style groups are identified based on the principal components of characteristics. Upon transforming characteristics into PCs, I find that styles constructed using a few high-eigenvalue PCs capture nearly all the returns delivered from high-dimensional characteristic models. This 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. Using PCs yields a cleaner representation of the latent cluster structure and the underlying common demand shocks. Taken together, these findings highlight the pervasive

[3]Furthermore, the negative correlation between characteristic complexity and style effect suggests that investor underreaction is unlikely to be the primary driver of my 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, my empirical results indicate the opposite pattern.

adoption of style investing and its systematic influence on financial markets.

As a corollary to the impact of style investing on individual stocks, I also investigate the implications at the aggregate market level. I hypothesize that aggregating the returns of style strategies is informative about market-wide mispricing. In particular, a widely and persistently high (low) return of the long (short) side of the style strategy implies heightened style-level purchasing (selling), thus suggesting market-wide overvaluation (undervaluation). Consequently, *both* the long- and short-side returns of style strategies are expected to be *negatively* associated with future market returns. I find supportive evidence for this corollary.

A series of additional tests are conducted to validate the robustness of my 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, I 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 both when considering styles within and across industries, suggesting the predictive ability of characteristics-derived style signal is not completely driven by industry-level positive feedback trading. Fourth, I examine style signals from alternative constructions and datasets, yielding similar results. Lastly, I conduct placebo tests by randomly categorizing stocks. As expected, the pervasiveness of predictability disappears for random styles.

Related literature. A large body of work provides empirical examinations of the seminal study by 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), within-style comovement (Barberis et al., 2005; Greenwood, 2008; Green and Hwang, 2009; Boyer, 2011; Hameed and Xie, 2019), and return predictability (Chen, 2003; 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., 2022) and large-scale examinations of stock return anomalies (McLean and Pontiff, 2016; Green et al., 2017; Chen et al., 2022a; Muravyev et al., 2022; Bowles et al., 2023). This paper introduces a

new stylized fact: returns are generally predictable through categorizing stocks into styles, even if the underlying characteristic lacks predictive ability.[4] Recent studies demonstrate the persuasiveness of high dimensionality and complexity over sparsity and parsimony in describing expected returns (Kozak et al., 2020; Giannone et al., 2021; Bessembinder et al., 2021; Kelly et al., 2022; Didisheim et al., 2023). Aligning with this perspective, my 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 synthesize multiple predictors for return forecasting (Gu et al., 2020; Cong et al., 2020; Chen et al., 2024; Bryzgalova et al., 2025). My 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 extension in 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 heterogeneity in style effects. Section 4 explores the commonality across styles and examines the role of dimensionality. Section 5 presents additional robustness tests. Section 6 concludes.

2 Styles and return predictability

My sample includes all common stocks (share codes 10 or 11) listed on NYSE, AMEX, and NASDAQ between June 1963 and December 2021. I obtain stock price data from CRSP and accounting data from COMPUSTAT. I 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 exhibit 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. I also obtain the q-factor (Hou et al., 2015) data from

[4]Nonetheless, caution is advised when interpreting these findings, as my 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.

the *Global-q* website.

2.1 Characteristics data and construction of style signals

The firm-level characteristics data are downloaded from the March 2022 release of the *Open Source Asset Pricing* (OSAP) dataset (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.[5] I begin with 204 "predictors", i.e., characteristics that have been shown to significantly predict future returns in their original papers, and 113 "placebos"– characteristics that do not exhibit clear predictive ability. To effectively utilize the data while maintaining a reasonable sample size, I 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 me with 312 firm characteristics in total.[6]

Figure 1 illustrates the timeline for constructing style signals and testing return predictability. At the end of each June, I 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, I assign stocks into $5\times N$ groups based on size and the characteristic if the number of categories (N) is less than 5. Otherwise, I continue to use the 5×5 assignment.[7] The resultant style assignments remain fixed throughout the following 12 months until the next June, at which point new style clusters will be identified. Each month, for each stock, I 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. Then, I form decile portfolios based on the constructed signal and examine the realized returns

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

[6]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.

[7]I use two-way clustering 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, I find that the predictive ability of style signals remains prevalent even when style groups are identified without the size dimension.

during the subsequent month.[8]

2.2 Performance of style-based strategies

I 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), the momentum-augmented factor model (FF6), and the q-factor model (Q4) of Hou et al. (2015). While I report both value-weighted and equal-weighted results, my main analysis relies on value-weighted portfolios.

Figure 2 presents the count of strategies exhibiting significant returns and those without. I 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, it is observed that nearly all style-based strategies earn significant returns under equal weighting. Overall, these results suggest the pervasive return predictability stemming from style categorization.[9]

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 reports 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 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 outlier styles being marked.[10] Consistent with previous studies, the value style (based on

[8] In the robustness section, I 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.

[9] Notably, style strategies either yield positive returns or returns that are negative but statistically indistinguishable from zero. Significantly negative returns are absent in the constructed strategies. In other words, style portfolios examined in this paper do not display short-term reversals.

[10] I use the characteristic acronym as in Chen and Zimmermann (2022) in presenting style variables. The

book-to-market) emerges as one of the strongest predictors. More importantly, BM is not the sole 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 can enrich the insights into style-induced price impacts.

2.3 Relation with characteristic-based strategies

A natural question arising from my findings is whether the performance of style portfolios depends on the predictive ability of the underlying characteristics. Figure 5 visually illustrates the relationship in performance between style-based strategies (SS) and characteristic-based strategies (CS). I consider both the ex-post (left panel) and ex-ante (right panel) performance of CS. Specifically, in the left panel, I 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, I consider the average CS returns in absolute value. In the right panel, I 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.

I further partition characteristics into two groups based on whether they display significant predict power in the extended sample (Panel A) or in the original sample (Panel B). Table 2 summarizes the conditional performance of SS. It shows that the strength of 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 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 I use the t-statistics reported in the original studies to partition characteristics.[11] 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 differs from the conventional characteristic-based model in its capacity to explain cross-sectional stock returns.

detailed description can be found in the *Signal Documentation* at `https://www.openassetpricing.com/data/`

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

3 Heterogeneity in style effects

In this section, I delve into the factors influencing the performance of style strategies. First, I examine the relationship between return comovement and return predictability across styles. Next, I investigate how the returns of style strategies vary with institutions' style trading. Third, I study the role of retail participation. Fourth, I show that characteristic attractiveness serves as a powerful predictor of strategy performance. Lastly, I leverage large language models to analyze textual information and examine how the complexity of a characteristic relates to style effect.

3.1 Comovement and profits of style strategies

The premise underlying the return predictability I study is style-level capital allocations. 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. A testable prediction can be derived from this basic mechanism. 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.

I 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, I 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. Suppose that 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 $Comove_{BM,t}$. I conduct this calculation each month for each style, which generates a panel of comovement measures.

Then, I estimate the following panel regression to examine the relationship between comovement and 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 comovement in the last month. I include time-fixed effects η_t and style-fixed effects γ_{style} in regressions.

Table 3 reports the results. In column (1), I include time-fixed effects and examine the cross-sectional variation of style strategy returns. Consistent with the my hypothesis, I 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), I 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), I use two-way clusters and re-estimate the t-statistics. It turns out that my result is not sensitive to these specifications and the estimated coefficient on $Comove_{style,t}$ is quantitatively similar.

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, I obtain firm-level institutional ownership data from the Thomson Reuters Institutional Managers (13F) Holdings database. The main reason I 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, I define the propensity of institutional trading (PIT) through quarterly cross-sectional regressions:

$$\Delta Inst_{i,q} = a_q + PIT_{style,q} R^{style}_{i,q} + b_q X_{i,q} + \varepsilon_{i,q}, \tag{2}$$

in which the dependent variable, $\Delta Inst_{i,q}$, is the quarterly change in stock i's institutional ownership.[12] The main independent variable $R^{style}_{i,q}$ is the cumulative style return of stock i over quarter q. The estimated coefficient, $PIT_{style,q}$, captures the extent to which institutional investor's trading aligns with the style signal. Specifically, a positive and larger $PIT_{style,q}$ 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.[13] Independent

[12] 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.

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

variables are lagged for one month relative to $\Delta Inst_{i,q}$.

Figure 6 presents the distribution of the estimated PIT. I calculate the average and median values of time series $\{PIT_{style,q}\}$, and then report the distributions of PIT for the 312 style signals. Consistent with the conjecture that institutions tend to trade at the style level, I find that the average PIT is positive for most signals. The median PIT 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 example. The average PIT 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% (0.10/6.65).

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

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

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

The positive relationship between PIT 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 PIT 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 PIT increases, thus mitigating mispricing.[14] However, I find a strongly positive predictive ability of PIT 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.[15]

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

[15]It's important to note that this conclusion is drawn from an average perspective. There is certainly a

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). On the other hand, institutions may engage in styles that attract retail investor interest to cater to their needs (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 stronger price impact for these styles. Analogous to the previous section, I estimate the propensity of retail trading (PRT) by monthly cross-sectional regressions:

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

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. I obtain retail trading volume data from the WRDS - TAQ Millisecond Tools database.[16] 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.[17]

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

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

and then conduct a cross-sectional regression:

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

The dependent variable, $\mathbb{E}[R_{style}]$, is the average style strategy return. If retail investors'

possibility that for some characteristics, the predictability is linked to fundamental news rather than style-driven investment. In a later analysis, I provide another test to further distinguish between style investing and underreaction based on complexities of characteristics.

[16] 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/`

[17] 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.

stronger response to past style returns is a signal of heightened style chasing, then one should expect a positive sign of the estimated β_1. I also control for the average propensity of institutional trading ($\overline{PIT}_{style}$) 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 PRT ($\hat{\beta}_1$) is positive and significant. For instance, column (1) of Panel A suggests that a one-standard-deviation increase in average PRT implies an increase in the average style strategy return of 3.4 bps (t=2.42). In columns (3) to (6), I control for the effect of institutional trading and comovement. Consistent with previous results, the estimated coefficients on the average PIT ($\hat{\beta}_2$) and the average comovement ($\hat{\beta}_3$) are positive and highly significant. Nevertheless, the average PRT still exhibits a positive and significant association with style strategy performance. In Panel B, I 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, I 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 outperforms, flows tilt toward the growth category. In both cases, heightened style demand amplifies price impact and lifts the return of the style strategy based on book-to-market. In other words, style investors chase price trends without strong priors about the characteristic's own predictive ability. This implies that style effects should be stronger as the *magnitude* of past characteristic returns increases, since the style becomes attractive.

To test this prediction, I define 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 return spread between the top and bottom book-to-market decile portfolios. Then, I conduct the following regression to examine the relationship between CRS and style effects:

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

where I control for comovement and the propensity of institutional trading studied in previous sections. If investors chase style performance rather than speculating anomaly returns, then we should expect a positive $\hat{\beta}_1$; moreover, the raw characteristic return without taking absolute value should exhibit no predictive power for style effects.

Table 6 reports the regression result. It shows that CRS is a strong predictor for style strategy returns both in the cross-section and time series. The first three columns of Panel A suggests 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 PIT does not alter this finding. In addition, columns (4) to (6) of Panel A show that the estimated coefficients on Comove and PIT remain significant and are comparable to previous estimates. This result suggests that CRS captures incremental information describing the price impact of style investing.[18]

Panel B of Table 6 tests a variety of alternative measures. First, I use raw characteristic returns instead of absolute values. The estimated coefficient is minor and insignificant (t=0.74). Second, I adjust the signs of characteristic returns based on the predictive power of characteristics, ensuring that their expected values are always positive.[19] Even after this adjustment, the signed characteristic returns exhibit no predictive power for style effects. Third, I find that style strategies display weak autocorrelations as lagged style strategy returns do not predict future returns. As a placebo test, I 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 variable choices are silent on 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 relationship detected in this section might emerge 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* 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).

[18] In addition, CRS differs from comovement and investors' propensity of trading (i.e., PIT and PRT) in that time-variations matter 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.

[19] I consider this adjustment since I 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, I 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).

3.5 Evaluating implementation complexity using LLM

Characteristics vary in their complexity, which is crucial for implementing trading strategies. For instance, characteristics such as 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 me to partially distinguish style investing from the underreation 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 my findings, however, higher complexity should imply stronger performance of style strategies. This is because highly complicated 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.[20] 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. I attempt to address this issue by leveraging recent developments in large language models (LLMs) to assess the complexities of characteristics.[21] Specifically, I obtain text-form detailed descriptions of each characteristic from the OSAP website. The descriptions provided by Chen and Zimmermann (2022) contain definitions, data requirements, and construction methods of characteristics. I then prompt OpenAI's ChatGPT-4o with these descriptions and request an evaluation of complexity by assigning a score to each characteristic, ranging from 1 to 3, with higher scores indicating greater complexity. Figure 7 illustrates the prompt used in this section. I use the default parameter setting of ChatGPT in my analysis. To account for potential variability and randomness in ChatGPT's responses, I submit the same prompt independently for 100

[20] 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.

[21] Research on using LLMs to extract information, generate evaluation and forecast, 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. (2024); and Kim et al. (2024).

rounds and calculate the average complexity score for each characteristic.[22]

To examine the relationship between implementation complexity and style effects, I 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, 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.[23] 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 (like 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 involve dividing accounting terms by market capitalization, while profitability calculations commonly involve computing revenues and costs. Therefore, I 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, whereas analyst forecasts require data from IBES. Thus, I also incorporate fixed effects for data categories. Additionally, I address the potential concern that complexity might correlate with the journal where 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

[22]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.

[23]The prompt depicted in Figure 7 also includes confidence levels for the assigned complexity scores. I 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, I focus solely on the complexity score in the analysis.

coefficient on complexity remains negative across all specifications.[24]

Overall, style-based pricing effects exhibit significant heterogeneity. The evidence thus far suggests that style strategy performance is stronger for characteristics with higher comovement, increased institutional trading, more retail participation, greater attractiveness, and low complexity—findings that align well with both economic theory and real-world financial market practices. In the next section, I investigate the interdependence between styles, and dimensionality in capturing the return predictability from style investing.

4 Commonality and dimension in style effects

It is inherent for styles to exhibit correlations. For instance, a trading strategy tilted toward high-tech firms will naturally load on companies with similar investment activity and valuation ratios. This interdependence underscores the need to identify style clusters in a high-dimensional space. This section characterizes the correlation structure across styles. Building on these results, I investigate the role of dimensionality in unveiling return predictability emanating from style investing.

4.1 Correlations between styles

As the empirical asset pricing literature discovers a huge set of anomalies in the cross-section, it remains an unsolved question that which firm characteristics truly provide independent information about expected returns (Cochrane, 2011). Recent studies, however, points 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 characteristics-derived style signals demonstrate significant predictive ability for returns, it is important to examine the interdependence of styles.

Figure 8 shows the distributions of pairwise correlations between styles. For style signals, I first calculate cross-sectional correlation coefficients and then take time-series averages; for style strategies, I simply compute the full-sample pairwise correlations between long-short portfolio returns. In sharp contrast to characteristic-based results, I find that style-based

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

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.[25]

To examine the commonality in style returns, I extract the principal components (PCs) from an eigenvalue decomposition of the covariance matrix of style strategies. I restrict attention to styles for which the underlying characteristic data is available from June 1980 and the full-sample strategy return is significant at the 5% level.[26] Following Kozak et al. (2018), I also conduct time-series regressions of each style strategy on the first K PCs. The second column of Table 8 reports the average R^2 for PCs 1 to 10. It shows that the first PC alone explains 57.6% of the time-series variation of style returns. As a comparison, PCs with lower eigenvalue 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, I find that the first PC explains a substantial portion (58.4%) of the time-series variation in strategy returns. Figure 9 graphically presents the cumulative ratio of the total variance of style strategies explained by PCs.

The first PC puts 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 9 visualizes the factor loadings of PC1 in descending order. The factor loading gradually decays for the first 250 styles and diminishes in a steeper way 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 8 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, I examine the role of dimensionality in style pricing. The fact that (1) the first PC explains a substantial portion of time-series variations of 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, I adopt a standard machine learning algorithm, k-means clustering, to construct style signals in a

[25] 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, it's likely that those within the same group will share similar y values, even though the linear correlation between x and y is minimal.

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

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):

$$W(\mathbb{C}) = \sum_{k=1}^{K} \sum_{\mathbf{x} \in C_k} \|\mathbf{x} - \mathbf{m}_k\|^2, \tag{9}$$

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, I 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 of d, I examine how the return predictability varies with the style dimensionality.

For a given number of dimensions d, an ideal implementation would be to go through 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 cost of computation 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.

I use a heuristic procedure to guide my empirical examination. Specifically, I rank individual styles in descending order based on their loadings on the first PC, which are calculated in the previous subsection. Then, I choose the first d variables (along with firm size) to construct the d-dimensional style and the associated return signal. For example, when $d = 2$, I use size, CF (cash flow-to-market), and IdioVolCAPM (idiosyncratic volatility) and apply the k-means clustering each June to identify style groups.[27] Analogously, the style signal for individual stocks is calculated as the value-weighted average return of other stocks within the same group. It's worth noting that while the computation of PCs and factor loadings relies on full-sample results, my approach does not directly utilize quantitative information. Rather, I rely solely on the extraction of ranks to guide the determination of

[27] In each computation, I standardize all characteristics cross-sectionally by mapping their ranks to the interval $[0, 1]$. For missing values, I 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.

which styles are incorporated in the construction process for a specific number of dimensions.

Figure 10 reports the performance of high-dimensional style strategies graphically. Similar to my baseline analysis, I 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 an annualized Sharpe ratio of around 1.16 (1.77).

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 return predictability driven by style investing-induced price impact.

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 adequately 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.

I modify the previous examination by first rotating stocks into the PC space before constructing style groups. To achieve this, each June, I 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 11 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 10, 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 literally 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 10 indicates that a large number of characteristics is necessary to reveal the potential return predictability. Nevertheless, Figure 11 suggests that a sparse representation in 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.[28] Since individual characteristics are noisy proxies, PCs of characteristics provide a parsimonious basis for the latent cluster structure and the coordinated style demand. As such, styles derived from high-eigenvalue PCs contribute substantially to the observed return predictability.

5 Additional tests

This section provides several additional tests. First, I examine market return predictability. Second, I assess 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. I also extend the analysis to two additional characteristic datasets to mitigate concerns about the potential noise in data. Finally, I conduct placebo tests to show that randomly generated styles exhibit no pricing effects.

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

5.1 Style investing and market trends

One important implication of Barberis and Shleifer (2003) pertains to long-horizon effects. If the positive feedback trading at the style-level exerts pressure on asset prices, pushing them away from fundamental values, then we should observe reversals in stock returns over the long term. Studies such as Teo and Woo (2004), Froot and Teo (2008), Greenwood (2008), and Jame and Tong (2014) indeed find evidence supporting such reversals at the style level.

In this section, I present an alternative test regarding the reversal effect of style investing. The use of large-scale style portfolios allows for a systematic measurement of misvaluation resulting from positive feedback trading. Intuitively, if long-side returns of style strategies are extensively and persistently high, then one would expect significant market overvaluation due to style chasing. Similarly, persistently low returns on the short side of style strategies indicate continued underpricing. That is, *both* the long- and short-side returns of style strategies should be *negatively* associated with future market returns. Moreover, given that short-sale constraints prevent investors from easily selling stocks with low-style returns, the association between style portfolio returns and market performance should be asymmetric. The price correction associated with the short-side of style strategies (undervaluation) would predominantly manifest in the short and medium terms; as a comparison, the overvaluation from the long-side style portfolios requires a longer horizon to alleviate.

I aggregate the style-based portfolio returns by first taking the cross-sectional median return and then calculating two-year rolling averages.[29] Figure 12 plots the long-side style return and subsequent market performance over the sample period. It shows that the market tends to move downward as the long-side style portfolios earn higher returns. To formally test my hypothesis, I conduct the following predictive regression:

$$Mkt_{t+1,t+h} = \alpha + \beta_1 \overline{R}_{long,t} + \beta_2 \overline{R}_{short,t} + Controls_t + \varepsilon_{t+1,t+h}, \tag{10}$$

in which the dependent variable $Mkt_{t+1,t+h}$ is the h-month ahead cumulative market excess return. The main independent variable of interest, $\overline{R}_{long,t}$ ($\overline{R}_{short,t}$), is the average of cross-sectional medians of the long (short)-side style strategy returns over the past two years. I also control for a battery of predictors in my regression, including the cumulative market excess return over the past two years (LMKT), the book-to-market ratio (BM), the dividend-to-price ratio (DP), the earnings-to-price ratio (EP), the default yield spread (DFY), the

[29] Since the moving average construction introduces autocorrelations mechanically, I test the aggregate style portfolio return for a unit root using an Augmented Dickey-Fuller (1979) test. The test statistic reject the null that the aggregate style portfolio return is non-stationary. The predictive regression result is also qualitatively similar when using a shorter estimation window such as 18 months, or using a longer estimation window such as 30 months, to calculate aggregate style portfolio returns.

term spread (TMS), stock variance (SVAR), investor sentiment (SENT), inflation (INFL), and the net equity expansion (NTIS).[30]

Table 9 reports the regression results. I find that past style portfolio returns significantly and negatively predict future market returns across various horizons. An increase in the long-side return of 1% implies a decrease in one-year ahead returns of around 7.5%. The effect persists for up to five years and is larger for long-term returns. For example, the slope of $\overline{R}_{long,t}$ is -0.130 (-0.137) when forecasting two (three)-year ahead market returns. For the short-side style return, the corresponding predictive ability is evident in a three-month to the one-year window. A decrease in the short-side return of 1% is associated with an increase in future market returns of around 3.4% to 6.9%. After controlling for the long-side return and other predictors, the estimated slope of $\overline{R}_{short,t}$ becomes insignificant over longer horizons.

Overall, I find evidence consistent with the long-run reversal implication of Barberis and Shleifer (2003), which suggests that a comprehensive set of styles from firm characteristics provides useful information on detecting market mispricing. The result also complements the finding of Dong et al. (2022) that anomaly returns jointly display predictive ability for market excess returns.

5.2 Residual style signals

Previous studies document that stocks within the same style group exhibit excess comovements (Barberis et al., 2005; Green and Hwang, 2009; Boyer, 2011). While I show that comovement is an important determinant of style strategy returns, the general positive correlation between style signals and focal firms' contemporaneous returns could undermine the estimation 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.

I 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 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 committing statistical

[30]The data on BM, DP, EP, DFY, TMS, SVAR, INFL, and NTIS are downloaded from Amit Goyal's website; SENT is downloaded from Jeffrey Wurgler's website. Since the predictive regression is performed using overlapping monthly observations, I use the Newey and West (1987) standard error and the Hodrick (1992) standard error to calculate the t-statistics, respectively.

significance at the 1% level. Overall, purging out the reversal effect in focal stocks' returns helps to strengthen the performance of style strategies.

5.3 Alternative portfolio specifications

The main results of this paper rely on decile portfolios formed by style signals with a share price cut-off 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, I examine the robustness of style pricing through several alternative portfolio specifications: (1) quintile portfolios instead of decile portfolios; (2) require a share price of at least \$5 instead of \$1; (3) quintile portfolios with a share price cut-off of \$5; (4) NYSE breakpoints when forming portfolios; (5) 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 my 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-statistics 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.

5.4 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 an industry-wide style investing behavior of 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 A2 reports the with- and cross-industry return predictability. Specifically, I assign stocks to industries based on the 4-digit SIC codes. Then, I calculate style signals as the value-weighted average returns of style peers within the same industry or in different industries. Consistent with my 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 a 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.

5.5 Alternative constructions and other characteristic datasets

I further assess the robustness of the style-based pricing effect through several other variations in empirical specifications. First, I 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. I test a simpler one-way sort construction. Specifically, each June and for each characteristic, I sort stocks into ten groups based on the characteristic, and compute style signals as value-weighted average returns of other stocks in the same decile.

Second, I 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, I 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).[31] For each dataset, I examine the predictive ability of derived style signals with the same construction as applied to the Chen and Zimmermann (2022) database.

Appendix Figure A3 shows that using single-dimension styles still yields pervasive 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.

5.6 A placebo test based on random styles

Finally, to further validate the economic significance of my findings, I conduct placebo tests using randomly generated style classifications. While I have shown the pervasive

[31]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. I am grateful to them for making these data available.

pricing effect of style investing, the performance of style strategies also exhibits economically meaningful heterogeneity. The findings in Section 3 suggest that a style is more likely to be responsible for asset pricing when it closely aligns with return comovement and investors' trading. Therefore, it is reasonable to expect that artificially constructed style signals, lacking economic foundation, should demonstrate minimal predictive power.

I implement this placebo test in two ways. First, I 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, I compute style signals as the value-weighted average monthly returns of other stocks within the same randomly assigned group. I then form decile portfolios based on these signals and evaluate long-short strategies that buy stocks in the top decile while selling those in the bottom decile. Panels (a) and (b) of Figure 13 depicts 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, to account for potential persistence in characteristics and hence style grouping, I construct pseudo-characteristics using the following AR(1) process:

$$X_{i,t} = \rho X_{i,t-1} + \epsilon_{i,t}, \tag{11}$$

where $X_{i,t}$ represents the characteristic value of i in June of year t, and $X_{i,t-1}$ is the value from the previous June. The persistence parameter ρ ranges from 0 to 1 (exclusive), and the noise term $\epsilon_{i,t}$ is i.i.d., following a normal distribution $N(0, \sigma)$. I consider 30 values of ρ within the interval $[0.01, 0.98]$ and 30 values of σ within the interval $[0.01, 0.50]$. As a result, a total of 900 (30×30) pseudo-characteristics are created, varying across persistence (ρ) and volatility (σ). For each pseudo-characteristic, I start the simulation by generating initial characteristic values for stocks from a standard normal distribution. These values are updated over time based on equation (11). Stocks are then categorized into 25 portfolios by sorting on the simulated characteristic value at the end of each June. Style signals and corresponding trading strategies are constructed following the same methodology as before.

Panel (c) of Figure 13 presents the performance distribution of style strategies derived from these pseudo-characteristics. Aligned with the findings from purely random number-based styles, approximately 86% of strategies fail to generate statistically significant returns. Panel (d) further investigates the relationship between strategy performance and the underlying parameters. It shows that even pseudo-characteristics exhibiting high persistence

and low volatility (i.e., high ρ with low σ) do not yield profitable style strategies.[32] Collectively, these placebo tests provide evidence that the documented style-based return predictability is unlikely to be an artifact of statistical noise or due to mechanical persistence in characteristics. Rather, its pervasiveness points to the price impact of style-driven trading.

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, I 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 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. It highlights 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 opens up new possibilities for research in the field.

[32] If any, the few instances of statistically significant style effects are observed among pseudo-characteristics with low persistence and high volatility. These results are more likely attributable to random chance rather than economic reasons.

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.

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. 2023. Anomaly time. *Available at SSRN 3069026* .

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

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.

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. 2003. On characteristics momentum. *The Journal of Behavioral Finance* 4:137–156.

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.

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

Dickey, D. A., and W. A. Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association* 74:427–431.

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

Dong, X., Y. Li, D. E. Rapach, and G. Zhou. 2022. Anomalies and the expected market return. *The Journal of Finance* 77:639–681.

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.

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.

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.

Hodrick, R. J. 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *The Review of Financial Studies* 5:357–386.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies* 28:650–705.

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.

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. 2022. Is there a replication crisis in finance? *The Journal of Finance* .

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

Kelly, B. T., S. Malamud, and K. Zhou. 2022. The virtue of complexity in return prediction. Tech. rep., National Bureau of Economic Research.

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.

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. 2022. Anomalies and their short-sale costs. *Available at SSRN 4266059* .

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.

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.

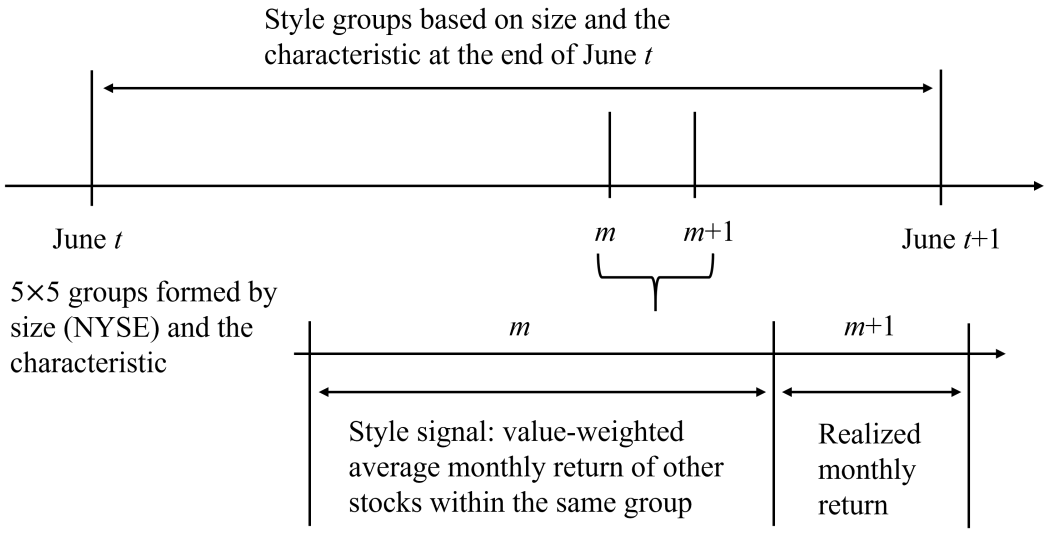


Figure 1. Timeline for signal construction and predictability tests
This figure illustrates the timeline for constructing style signals and testing their ability to predict future stock returns. At the end of each June, style groups are defined by sorting stocks into 5×5 portfolios based on market capitalization (NYSE breakpoints) and one of the 312 characteristics. The resulting style groups are fixed in 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.

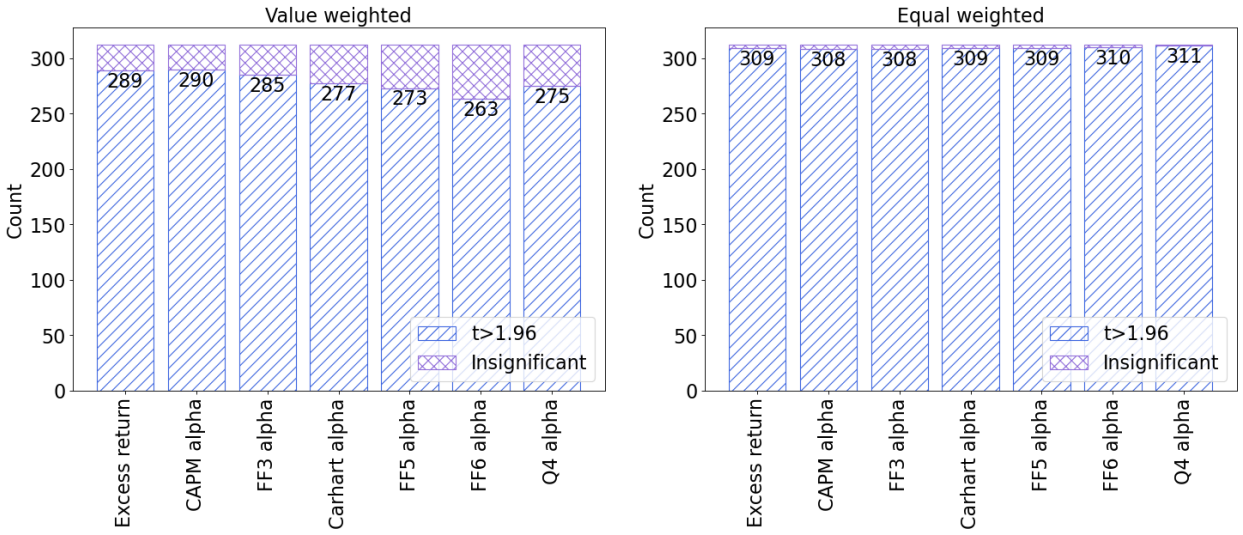


Figure 2. Summary of style strategy performance

This figure reports the number of style strategies with significant mean returns ($t > 1.96$) and insignificant returns. For each style signal, I 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. I 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), the momentum-augmented factor model (FF6), and the q-factor model (Q4) of Hou et al. (2015). The t-statistics are calculated based on Newey-West adjusted standard errors. The sample period is from July 1963 to December 2021.

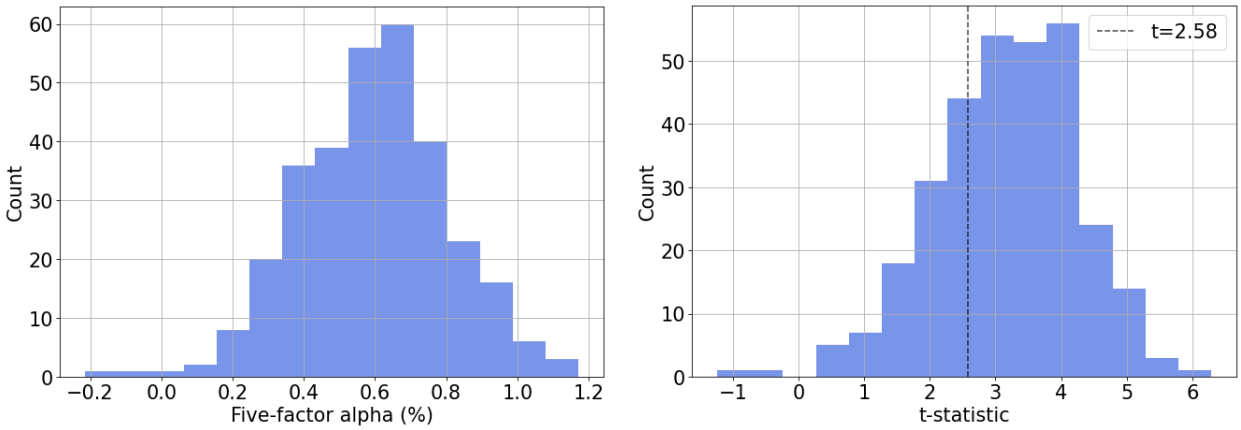


Figure 3. Performance distribution of style strategies
This figure shows the distributions of returns (left) and t-statistics (right) of the 312 style strategies. Returns are adjusted based on the five-factor model of Fama and French (2015) and the t-statistics are calculated based on Newey-West adjusted standard errors. The sample period is from July 1963 to December 2021.

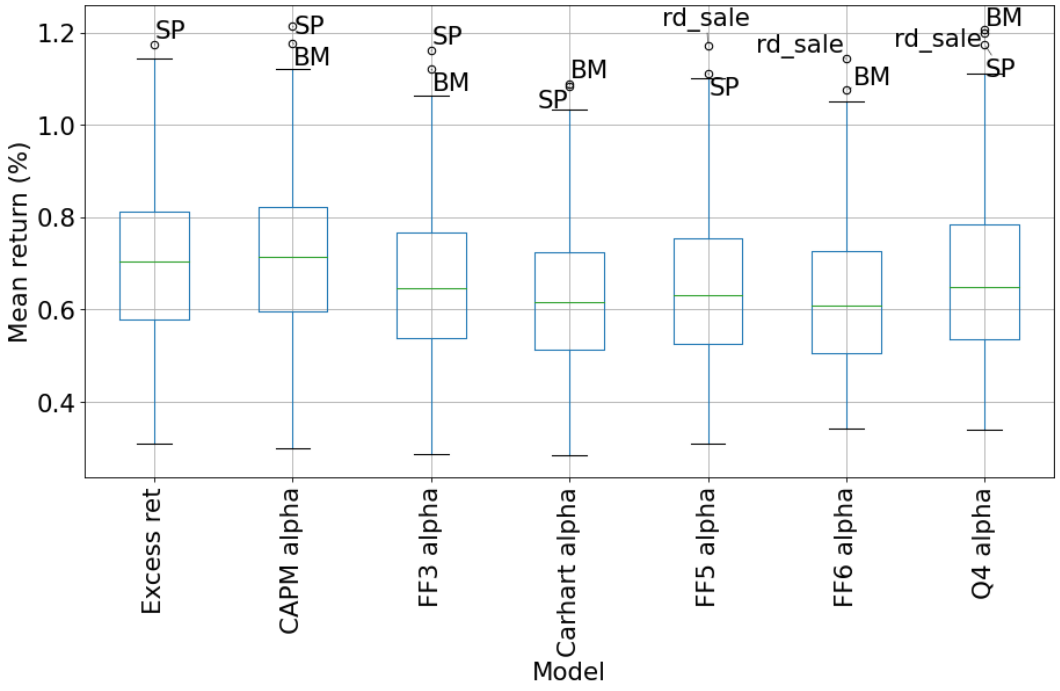


Figure 4. Style portfolio performance by asset pricing models

This figure shows the performance of style strategies by benchmark models. The sample is restricted to strategies with significant average returns. The middle line is the median and the boxes are 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 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).

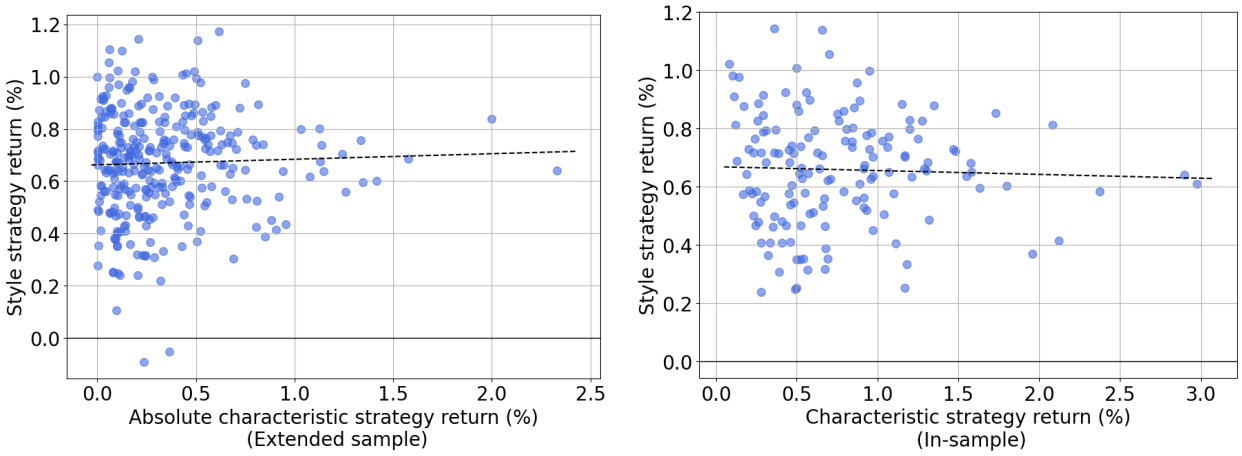


Figure 5. Mean returns of style-based and characteristic-based strategies

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.

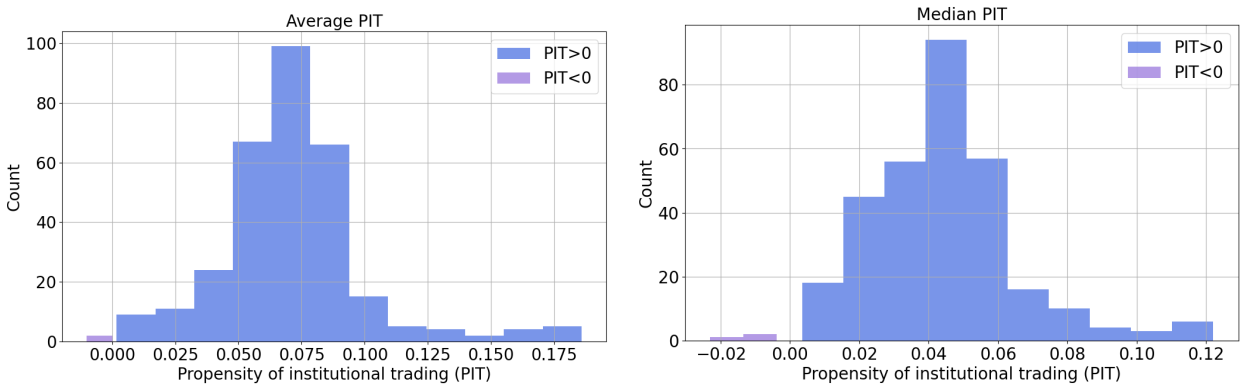


Figure 6. Distributions of estimated PIT

This figure reports the distributions of the propensity of institutional trading (PIT). PIT is estimated based on equation (2). I calculate the average and median PIT (multiplied by 100) for style signals and report the distributions of 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 prompt is made to OpenAI's ChatGPT-4o model.

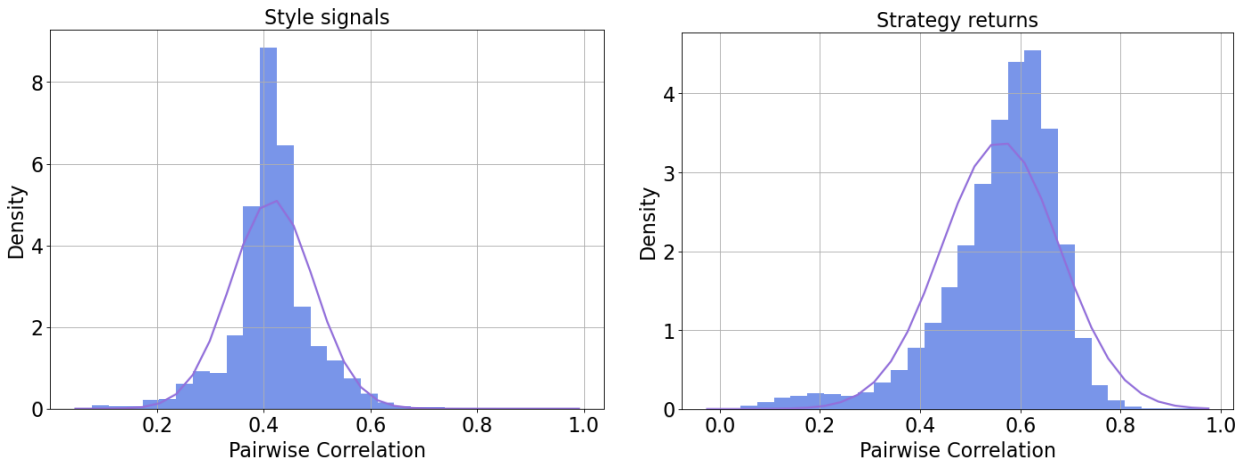


Figure 8. Correlations between styles

This figure reports the distributions of pairwise correlations between style signals (left) and between style strategy returns (right). The sample period is from July 1963 to December 2021.

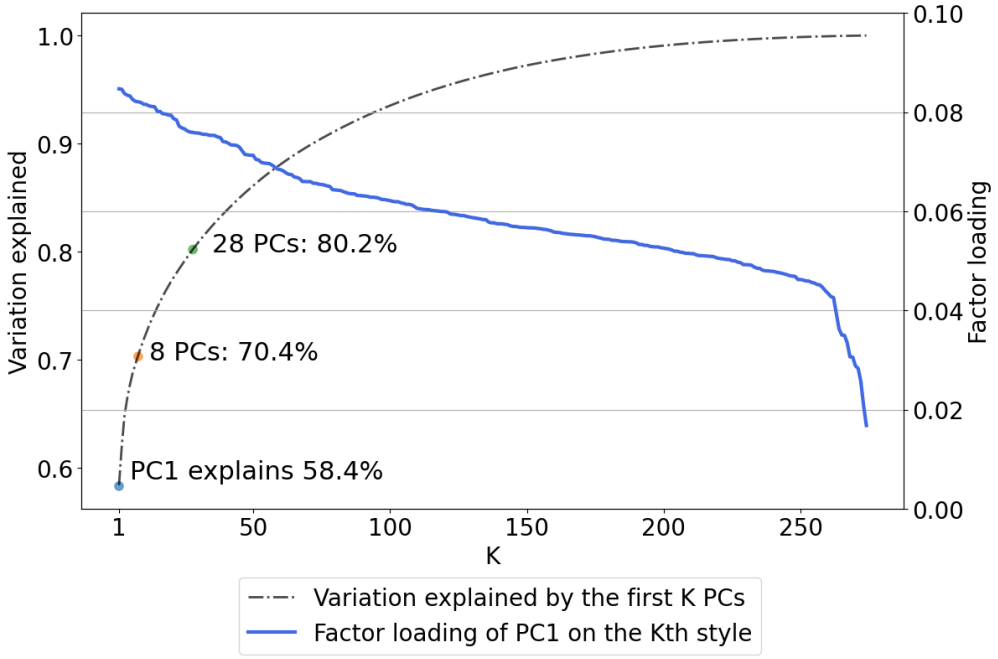


Figure 9. PCA of style strategies

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.

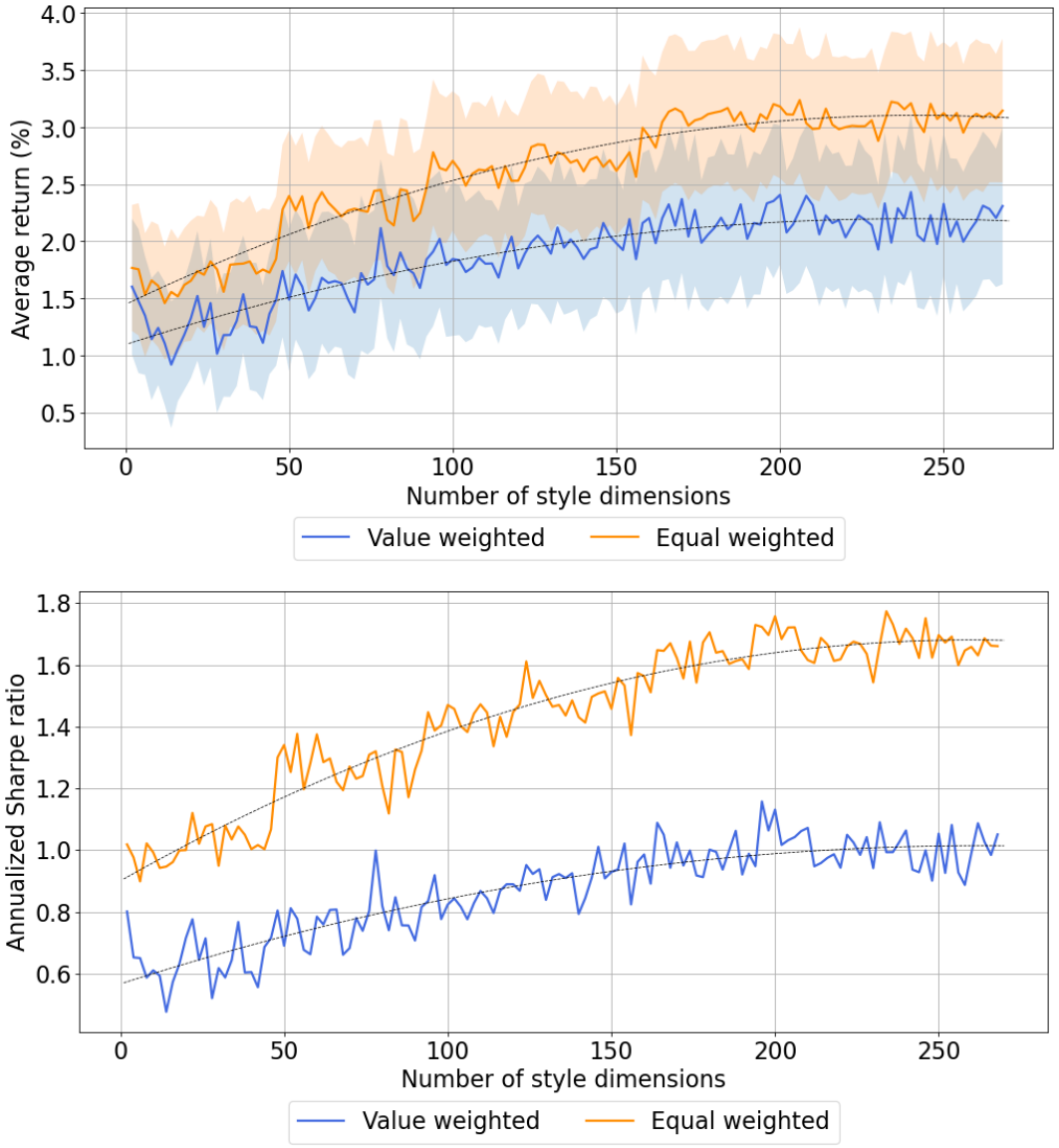


Figure 10. Style dimension and return predictability

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. I 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 shadow areas in the upper panel represent the 95% confidence intervals. The sample period is from July 1980 to December 2021.

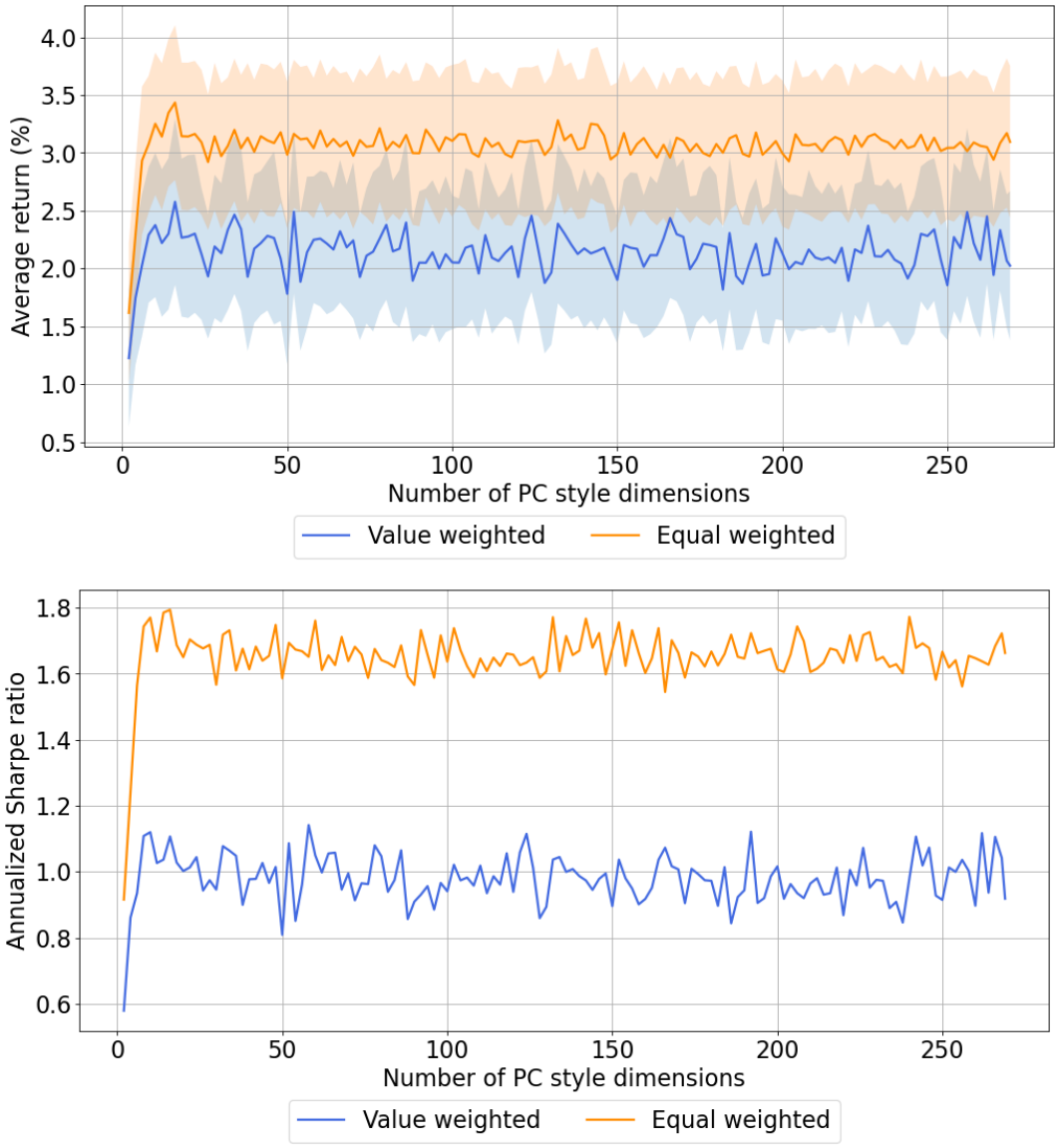


Figure 11. PC styles and return predictability

This figure plots the performance of style strategies as a function of the number of PC style dimensions. Each June, I calculate the principal components (PCs) of characteristics and then catogorize stocks into 50 groups based on the first d PCs, using the k-means clustering. The style signal is the value-weighted average monthly return of other stocks in the same PC style group. I 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 shadow areas in the upper panel represent the 95% confidence intervals. The sample period is from July 1980 to December 2021.

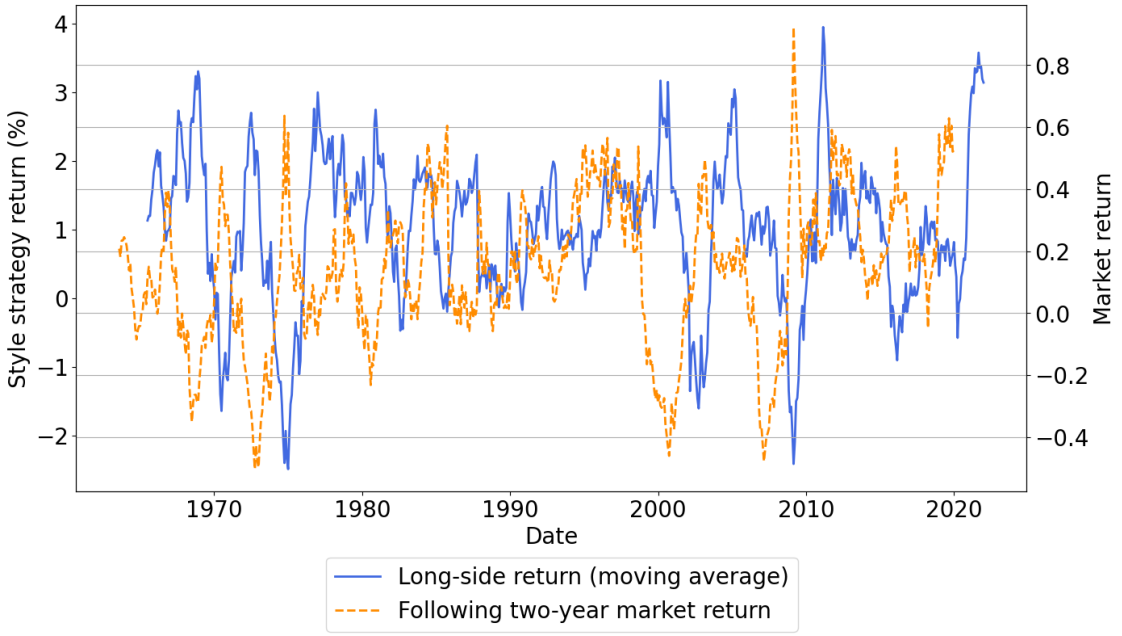
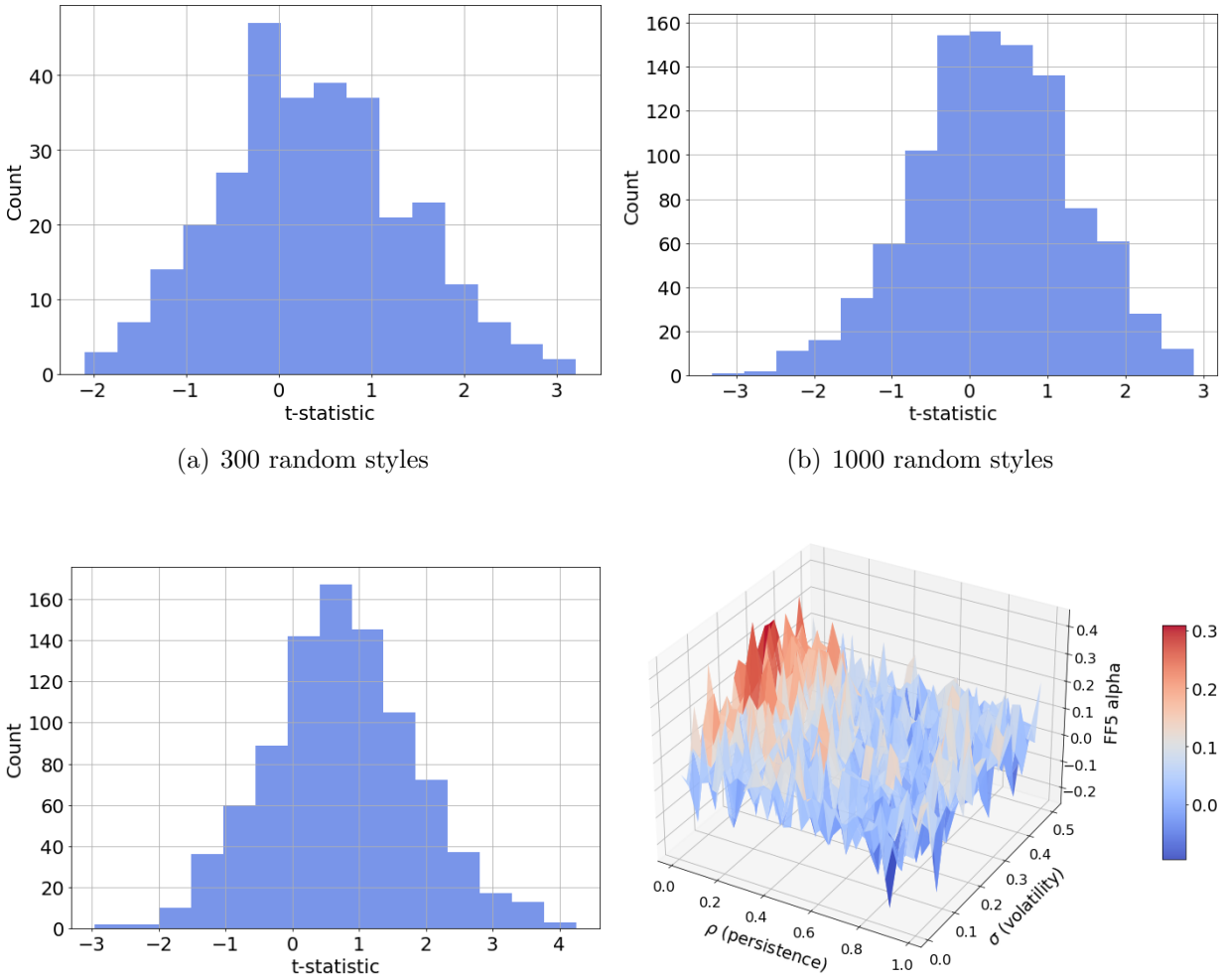


Figure 12. Style strategy returns and future market performance

This figure plots the aggregate long-side style strategy returns and subsequent two-year cumulative market returns. To construct aggregate style strategy returns, I first calculate cross-sectional median returns of style strategies and then compute two-year moving averages. The sample period is from July 1963 to December 2021.



(a) 300 random styles

(b) 1000 random styles

(c) 900 styles from pseudo-characteristics

(d) Return variations across pseudo-characteristics

Figure 13. Performance distribution of random style strategies

This figure shows the performance of random style strategies. In Panels (a) and (b), style classifications are constructed by grouping stocks based on randomly assigned numbers. In Panels (c) and (d), style classifications are generated using pseudo-characteristics, as defined in equation (11). Specifically, Panels (a), (b), and (c) present the distribution of strategy t-statistics, whereas Panel (d) depicts the relationship between strategy returns and the parameters of the underlying pseudo-characteristics (persistence ρ and volatility σ). Strategy returns are adjusted using the Fama and French (2015) five-factor model, and the t-statistics are calculated based on Newey-West adjusted standard errors. The sample period is from July 1963 to December 2021.

Table 1. Summary of style strategy performance

This table reports the summary statistics of style strategies. In Panel A and Panel B, strategies are restricted to those having 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 results based on the average excess 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), the momentum-augmented factor model (FF6), and the q-factor model (Q4) of Hou et al. (2015). The t-statistics are calculated based on Newey-West 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	Q4 alpha
Panel A. Average return (%)							
Mean	0.699	0.713	0.655	0.626	0.643	0.624	0.667
Std.Dev.	0.171	0.176	0.168	0.158	0.169	0.162	0.182
Min	0.309	0.299	0.285	0.283	0.310	0.342	0.338
Median	0.703	0.715	0.646	0.615	0.631	0.607	0.649
Max	1.173	1.213	1.160	1.087	1.172	1.143	1.206
N	289	290	285	277	273	263	275
Panel B. t-statistic							
Mean	3.830	3.881	3.805	3.476	3.445	3.308	3.219
Median	3.840	3.961	3.843	3.424	3.416	3.289	3.116
Std.Dev.	0.964	0.986	0.980	0.862	0.846	0.800	0.748
Proportion ($t \geq 3$)	0.761	0.769	0.765	0.682	0.681	0.608	0.585
Proportion ($t \geq 2.58$)	0.882	0.879	0.863	0.816	0.806	0.802	0.775
N	289	290	285	277	273	263	275
Panel C. All styles							
Mean average return (%)	0.670	0.684	0.623	0.586	0.594	0.567	0.624
Median average return (%)	0.681	0.700	0.634	0.595	0.606	0.573	0.616
Mean t-stat	3.644	3.695	3.588	3.234	3.173	3.000	3.007
Median t-stat	3.770	3.821	3.705	3.281	3.259	3.041	3.029
N	312	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-West adjusted standard errors. In Panel B, the t-statistics of CS are obtained from the original studies.

	Excess return	CAPM alpha	FF3 alpha	Carhart alpha	FF5 alpha	FF6 alpha	Q4 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	0.915
# $\lvert t_{CS}\rvert \geq 1.96$	118	159	159	131	137	114	94
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	0.867
# $\lvert t_{CS}\rvert < 1.96$	194	153	153	181	175	198	218
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	0.574
# $\lvert t_{CS}\rvert \geq 2.58$	74	107	114	84	88	72	54
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	0.705
# $\lvert t_{CS}\rvert < 2.58$	238	205	198	228	224	240	258
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	0.896
# $\lvert t_{CS}\rvert \geq 1.96$	173	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	0.880
# $\lvert t_{CS}\rvert < 1.96$	25	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	0.694
# $\lvert t_{CS}\rvert \geq 2.58$	147	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	0.784
# $\lvert t_{CS}\rvert < 2.58$	51	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 trading and style strategy returns

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

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

The independent variable $PIT_{style,t}$ is calculated from quarterly panel regressions based on equation (2). Regressions also include the magnitude of comovement of each style ($Comove_{style,t}$) 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)
PIT	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 trading and style strategy performance
This table reports the results from cross-sectional regressions:

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

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 trading ($\overline{\text{PRT}}$) of the corresponding style, as calculated using equations (4) and (5). Control variables include the average propensity of institutional trading ($\overline{\text{PIT}}$) and the average comovement ($\overline{\text{Comove}}$) associated with the style. I 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						
$\overline{\text{PRT}}$	0.034	0.039	0.039	0.042	0.020	0.027
	(2.42)	(2.74)	(2.95)	(3.08)	(2.05)	(2.72)
$\overline{\text{PIT}}$			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 Sharp ratio						
$\overline{\text{PRT}}$	0.019	0.029	0.025	0.033	0.014	0.024
	(1.90)	(2.71)	(2.65)	(3.23)	(1.94)	(2.97)
$\overline{\text{PIT}}$			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 lagged characteristic-return spread (CRS):

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

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 inclues comovement (Comove) and the propensity of institutional trading (PIT) 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 characteristics-based strategies; (2) returns from characteristics-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)
PIT					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, I consider control variables studied in previous sections, including the average propensity of institutional trading ($\overline{\text{PIT}}$), the average propensity of retail trading ($\overline{\text{PRT}}$), the average comovement ($\overline{\text{Comove}}$), and the avereage 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)
$\overline{\text{PIT}}$		0.032			
		(2.62)			
$\overline{\text{PRT}}$			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. 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, descriptive information, 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 (3 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

Table 9. Style effects and future market returns

This table reports results from predictive regressions:

$$Mkt_{t+1,t+h} = \alpha + \beta_1 \overline{R}_{long,t} + \beta_2 \overline{R}_{short,t} + Controls_t + \varepsilon_{t+1,t+h}.$$

The dependent variable ($Mkt_{t+1,t+h}$) is the h-month ahead cumulative market excess return and the main independent variables of interest, $\overline{R}_{long,t}$ and $\overline{R}_{short,t}$, are the two-year rolling average of cross-sectional medians of long-side and short-side style strategy returns (multiplied by 100), respectively. Control variables include the cumulative market excess return over the past two years (LMKT), the book-to-market ratio (BM), the dividend-to-price ratio (DP), the earnings-to-price ratio (EP), the default yield spread (DFY), the term spread (TMS), stock variance (SVAR), investor sentiment (SENT), inflation (INFL), and the net equity expansion (NTIS). The t-statistics based on Newey and West (1987) standard errors with a lag length of h months (NW t) and the Hodrick (1992) standard errors (Hodrick t) are reported in parentheses. The sample period is from July 1963 to December 2021.

	(1) h=3	(2) h=6	(3) h=9	(4) h=12	(5) h=18	(6) h=24	(7) h=30	(8) h=36	(9) h=48	(10) h=60
$\overline{R}_{long,t}$	-0.013	**-0.031**	**-0.054**	**-0.075**	**-0.109**	**-0.131**	**-0.135**	**-0.137**	**-0.138**	**-0.152**
NW t	(-1.65)	**(-2.33)**	**(-3.14)**	**(-3.61)**	**(-4.08)**	**(-4.80)**	**(-4.42)**	**(-4.38)**	**(-2.86)**	**(-2.06)**
Hodrick t	(-1.41)	**(-1.77)**	**(-2.14)**	**(-2.33)**	**(-2.40)**	**(-2.36)**	**(-2.13)**	**(-2.03)**	**(-1.95)**	**(-1.93)**
$\overline{R}_{short,t}$	**-0.035**	**-0.062**	**-0.073**	**-0.071**	-0.053	-0.024	0.043	0.100	0.170	0.156
NW t	**(-2.69)**	**(-3.20)**	**(-3.22)**	**(-2.71)**	(-1.54)	(-0.50)	(0.68)	(1.19)	(1.47)	(1.30)
Hodrick t	**(-2.15)**	**(-2.12)**	**(-1.77)**	(-1.40)	(-0.81)	(-0.30)	(0.46)	(0.91)	(1.29)	(1.20)
Controls	√	√	√	√	√	√	√	√	√	√
N	675	672	669	666	660	654	648	642	630	618
Adj. R^2	0.07	0.16	0.23	0.29	0.35	0.39	0.44	0.48	0.51	0.51

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: Within- and cross-industry style pricing.
- Figure A3: 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

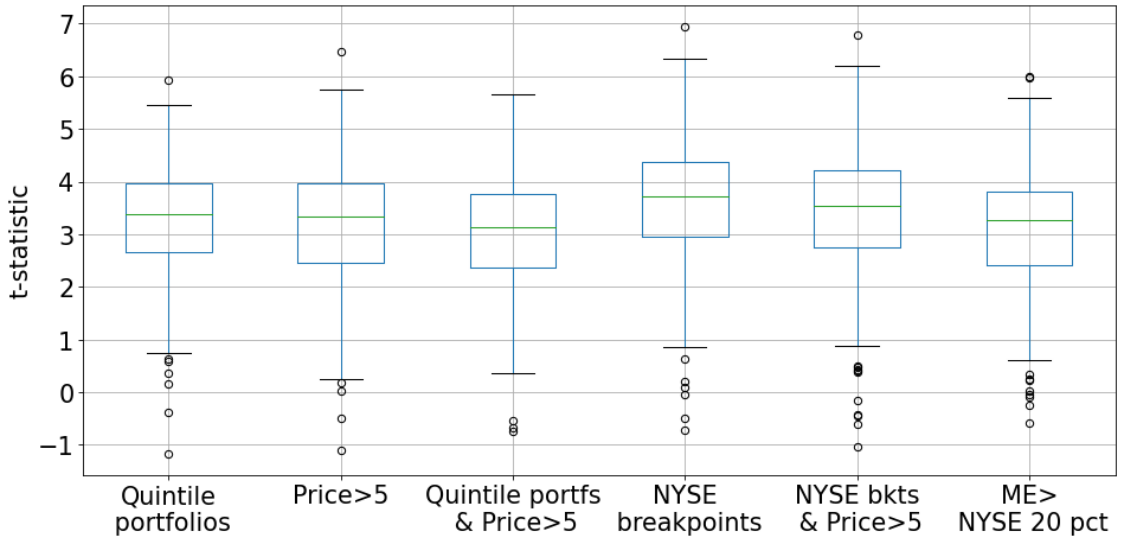


Figure A1. Style pricing under alternative portfolio specifications

This figure plots the t-statistics of 312 style strategies under alternative portfolio specifications. The middle line is the median and the boxes are 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-West standard errors and the sample period is from July 1963 to December 2021.

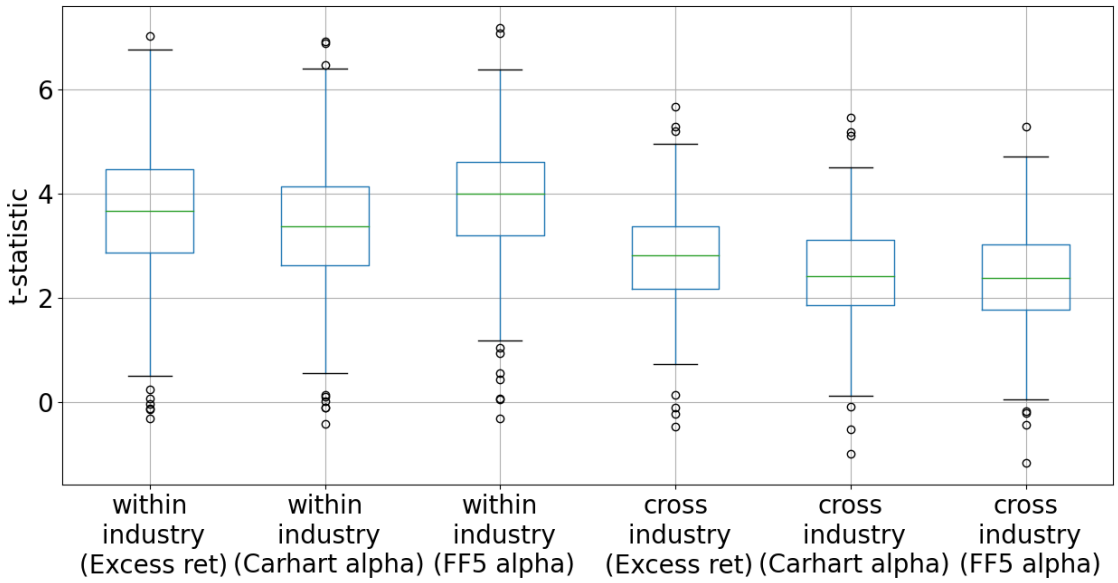


Figure A2. Within- and cross-industry style pricing

This figure plots the t-statistics of 312 style strategies for which the return signals are calculated as value-weighted average returns of style peers within the same industry or in different industries. Industries are defined based on the 4-digit SIC codes. The middle line is the median and the boxes are 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-West standard errors and the sample period is from July 1963 to December 2021.

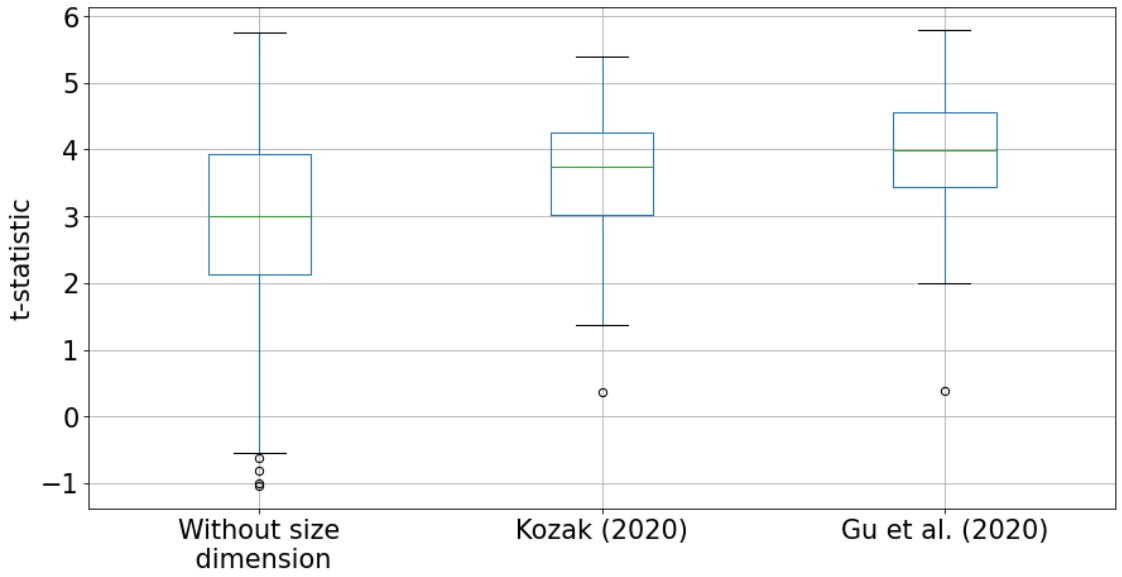


Figure A3. Style pricing under alternative style constructions and data sources This figure plots the t-statistics of style strategies under alternative style constructions and characteristic datasets. The middle line is the median and the boxes are 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within the 25th (75th) percentile minus (plus) 1.5 times the interquartile range. The t-statistics are based on Newey-West 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, I employ signed Sharpe ratios by adjusting characteristic returns to ensure positive expected values. In cases where characteristics lack clear return predictability, I utilize the absolute value of average returns when computing the signed Sharpe ratio. I 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-West 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	Q4 alpha
Panel A. Average return (%)							
Mean	0.752	0.759	0.689	0.679	0.679	0.667	0.707
Std.Dev.	0.175	0.177	0.169	0.165	0.167	0.169	0.182
Min	0.348	0.361	0.322	0.305	0.292	0.286	0.333
Median	0.758	0.763	0.692	0.668	0.661	0.647	0.685
Max	1.238	1.261	1.197	1.162	1.170	1.161	1.240
N	294	292	289	288	279	282	289
Panel B. t-statistic							
Mean	4.099	4.123	4.031	3.799	3.711	3.597	3.528
Median	4.220	4.212	4.123	3.823	3.742	3.575	3.513
Std.Dev.	1.034	1.042	1.031	0.951	0.903	0.901	0.835
Proportion ($t \geq 3$)	0.813	0.822	0.799	0.747	0.767	0.723	0.709
Proportion ($t \geq 2.58$)	0.901	0.894	0.896	0.889	0.857	0.851	0.851
N	294	292	289	288	279	282	289