Pervasive Styles *

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Abstract

This paper studies the price impact of positive feedback trading from style investing (Barberis and Shleifer, 2003). Employing a comprehensive set of 312 firm characteristics, I show that a majority (over 80%) of style-based trading strategies yield significantly positive profits, even for characteristics without any predictive power for returns. The style pricing effect is stronger under conditions of: (1) increased return comovement; (2) heightened institutional trading; (3) more retail chasing; (4) greater attractiveness of characteristics; and (5) low implementation hurdle as evaluated by ChatGPT. In addition, constructing styles within 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

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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 are prone to employ categorical thinking because of limited attention (Peng and Xiong, 2006), whereas institutions commonly group assets based on "styles" to specialize investment strategies and cater to attention. This style-level capital allocation induces comovement beyond what is justified by fundamentals; the price pressure from pursuing style performance generates predictability in asset returns. 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).

While value (e.g., book-to-market ratio) stands as perhaps the most widely adopted dimension for both practitioners and academics in identifying styles, an open question persists: Is the observed pricing effect susceptible to publication bias, and do alternative characteristics yield comparable effects? First, investment strategies, and hence styles, are highly diverse and heterogeneous (Kacperczyk et al., 2005; Buffa and Hodor, 2023; Pavlova and Sikorskaya, 2023). As such, value should not be the sole style generating substantial market impacts. Second, the real demand function for assets is usually unobservable. Initiating a trading strategy invariably involves integrating information from multiple characteristics. Thus, even a single investment style would indirectly affect the pricing of stocks within other categories. Furthermore, recent studies such as Kozak et al. (2020), Giannone et al. (2021), Chen and McCoy (2022), and Didisheim et al. (2023) demonstrate a high-dimensionality nature in explaining expected stock returns, suggesting that incorporating additional features yields economic benefits. Therefore, an empirical examination of the style-based pricing effect, 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.[1] Notably, the style-pricing effect does not rely on the underlying characteristics' predictive power for returns. Second and most important, I explore the determinants of style effect strength. While

[1]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.

return predictability is widespread, there exists substantial *heterogeneity* that aligns with style investing theories. Third, I assess the extent to which these styles can be captured in a parsimonious model, given their *common* underlying driver, namely, style investing behavior. I show that the principal components of characteristics can serve as representative styles that capture the potential return predictability associated with style investing.

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, 2021). For *each* characteristic, I construct style groups using size-characteristic grids and calculate firm-level style signals by averaging returns of a stock's style peers. Then, I sort stocks based on style returns and form long-short strategies that buy stocks within the top decile and sell those within the bottom decile. Among the 312 styles examined, I find that 289 trading strategies, using value-weighted portfolios, generate positive returns that are significant at the 5% level. The number of strategies exhibiting statistical significance ranges from 263 to 290 when returns are adjusted using various factor models. This indicates that a minimum of 84% of the style signals commit predictive ability for stock returns. The effect is more pronounced for equal-weighted portfolios, with almost all (over 98%) signals predicting returns positively and significantly.

The style pricing effect exhibits both statistical and economic significance. A substantial proportion of style strategies yield t-statistics exceeding 3, a threshold suggested by Harvey et al. (2016). Among strategies achieving significance at the conventional level ($t \geq 1.96$), the mean annualized return stands at 8.4%, with more than half producing factor-adjusted annualized returns larger than 7.2%. Additionally, while confirming that the book-to-market ratio is indeed an important style dimension, I also discover alternative characteristics that demonstrate comparable performance. These findings highlight how the diverse array of investment styles employed in practice exerts substantial influence on asset prices.

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 remains largely unrelated to the profitability of characteristic strategies. In particular, the correlation in average profits between style-based and characteristic-based strategies approaches zero. When I partition characteristics into groups based on their predictive ability for returns (both ex-ante and ex-post), the derived style strategies consistently generate significant returns regardless of the underlying characteristic's predictive power.

Having established the prevalence of style-based pricing effects, I turn to investigate their key determinants. Theoretical frameworks (e.g., Barberis and Shleifer (2003)) suggest that style investing creates return comovement because of coordinated demand, while 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 return predictability. Consistent with my conjecture, I find that styles with higher comovement effects earn 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), apparently, exhibit varying degrees of importance within the practical construct of style investing. Therefore, the pricing effect of a style should be more evident if it is widely used in designating 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 the shift in institutional demand for focal stocks aligns with style signals, then it indicates a higher likelihood of style chasing and thus stronger price impact.

I measure the propensity of institutional trading (PIT) on styles by regressions of changes in institutional ownership on each style signal. 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 styles reflects the slow dissemination of 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. In addition, I also estimate the propensity of retail investors toward style trading. I find that a heightened tendency for retail investors to chase style trends also corresponds to stronger style pricing effects.

Style investing also posits that investors categorize stocks based on characteristics without speculating on their profitability. Rather, the transient fluctuation in relative returns across categories motivates 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 converse case is also true in that investors would like to chase the trend of

growth stocks if they significantly outperformed value stocks. In either scenario, the style strategy based on the value characteristic (i.e., the book-to-market ratio) tends to yield higher returns. Consistently, I show that the *absolute* value of past characteristic strategy return positively predicts future style effects, whereas alternative proxies such as the raw characteristic return or lagged style strategy return exhibit no predictive power.

The last factor I examine is the complexity of characteristics. Implementation complexity 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 systematically evaluate the complexity of 312 characteristics based on their detailed textual descriptions. I show that characteristics with lower complexity are associated with stronger performance of the corresponding style strategy. This finding supports the hypothesis that characteristics that are conceptually clear, computationally simple, and readily accessible are more favorable in style investing.[2]

As I document the prevalent existence 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. It turns out that style signals (portfolio returns) are highly correlated with each other, and the correlation coefficients cluster around 0.40 (0.60). 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, 2021; Chen and McCoy, 2022). In addition, the first principal component (PC) explains a substantial portion (around 58%) of the variation in style returns. However, the correlation between styles does not posit that a parsimonious model with a few characteristics is sufficient in describing the derived return predictability, as the first PC puts positive and nearly equal weights on most styles.

To further investigate the role of dimensionality in style-induced return predictability, I employ k-means clustering, a standard machine learning algorithm, to construct high-dimensional styles. 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

[2]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.

strategy return and Sharpe ratio tend to increase in d, and more than 200 characteristics are necessary to reach the potential 30% annualized returns (value-weighted) and 1.20 annualized Sharpe ratios. While constructing style signals in high-dimensional characteristic spaces circumvents the need for 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, 2022).

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 result resonates with Kozak et al. (2020), who find that a sparse PC-based model performs well in describing cross-sectional returns based on a large number of characteristics. The observed high dimensionality of characteristics-based styles aligns with the pervasive adoption of style investing in asset management, while the sparsity in PC-based styles suggests underlying commonalities in style investing behavior and their systematic impacts on return dynamics.

As a corollary to the impact of style investing on individual stocks, I also investigate the implications of style pricing at the aggregate market level. I hypothesize that aggregating the returns of style strategies is informative about market-level 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.

I also perform additional tests to validate the robustness of my main results. 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 style-induced return predictability exists both within- and cross-industries. While the strategy performance is generally improved if styles are augmented with industry classifications, the predictive ability of style signals derived from characteristics is not completely driven by industry-level style investing. Fourth, I examine style signals from alternative constructions and datasets, which

yield similar results. Lastly, I conduct a placebo test using styles from randomly categorizing stocks. It turns out that the pricing effect disappears for most random styles.

Related literature

An emerging literature provides empirical examinations of the theoretical predictions of 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). I expand the set of candidate styles beyond value, size, and industry classification. Through a comprehensive examination of style portfolios based on a large number of firm characteristics, I show that the pricing effect of style investing might be more extensive and profound than the conclusions obtained in previous studies. My result suggests that the degree of comovement and institutional trading is positively related to return predictability, which is consistent with the underlying promise of the pricing implication of style investing.

A prominent feature in the area of empirical asset pricing is the emergence of meta-studies (Hou et al., 2020; Chen and Zimmermann, 2021; Jensen et al., 2022) and large-scale examinations of stock return anomalies (McLean and Pontiff, 2016; Green et al., 2017; Kim et al., 2021; Chen et al., 2022a; Muravyev et al., 2022; Bowles et al., 2023). While a consensus regarding the source of anomalies is far from reach, this paper introduces a new stylized fact: returns are predictable through categorizing stocks into styles, *even if* the underlying characteristic lacks predictive ability.[3] Recent studies also 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 emphasize the necessity of identifying styles within a high-dimensional space to capture the pricing implications of the diverse and complex investment strategies in practice. Notably, a sparse representation of style clusters becomes feasible when working in the PC space, complementing the insights of Kozak et al. (2020).

[3]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.

Several studies examine return predictability by combining multiple firm characteristics. He et al. (2021) define "similar stocks" using the Euclidean distance based on 5 characteristics, while Seyfi (2022) identifies "neighboring assets" using 94 characteristics.[4] They show that past returns of the thus-defined peer stocks positively predict focal stocks' future returns. While He et al. (2021) motivate their construction by the experience effect (Hertwig et al., 2004; Huang, 2019) and Seyfi (2022) pursues a pure return forecasting approach, this paper takes a fundamentally different perspective. Rather than attempting to construct a superior return predictor, this study conducts a comprehensive analysis of individual style strategies while examining how dimensionality reveals return predictability. Specifically, I investigate the heterogeneity and commonality across different investment styles and their broader implications for market behavior.

This paper also contributes to the literature on machine learning (ML) applications in asset pricing. ML algorithms' high-dimensional nature enables flexible and powerful modeling of conditional expected returns. An expanding body of research employs ML methods to synthesize multiple predictors for return forecasting (Gu et al., 2020; Cong et al., 2020; Gu et al., 2021; Han et al., 2022; Chen et al., 2023). My result suggests that large economic gains are achievable even when the training process does not explicitly target return prediction. This effectiveness stems from complex models' ability to approximate composite styles that emerge from the capital allocation patterns of sophisticated and heterogeneous investment strategies. The enhanced return predictability arises from a more refined representation of the underlying stock cluster structure. Recently, Bryzgalova et al. (2020) develop a tree-based algorithm to build basic assets that span the stochastic discount factor, while Cong et al. (2023) introduce the Bayesian Clustering Model that tackles the general grouped heterogeneity problem. These methodological advances offer promising avenues for extension in style portfolio construction.[5]

The rest of the paper is organized as follows. Section 2 describes the data sources and variable constructions, and summarizes 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. I conclude in Section 6.

[4]Specifically, He et al. (2021) use price, size, the book-to-market ratio, operating profitability, and investment; Seyfi (2022) employs 94 characteristics studied by Green et al. (2017) and Gu et al. (2020).

[5]Deep learning-based clustering is another promising approach for uncovering style representations of the stock market. See, for example, Aljalbout et al. (2018); Min et al. (2018); Ezugwu et al. (2022).

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 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, 2021). This dataset provides comprehensive coverage of the characteristics studied in Harvey et al. (2016), McLean and Pontiff (2016), Green et al. (2017), and Hou et al. (2020), thereby offering an expansive repository of information related to stock returns.[6] 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.[7]

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 remain

[6]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.

[7]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 (2021) 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.

to use the 5×5 assignment.[8] 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 and for each stock, the style signal corresponding to a specific characteristic is defined as the value-weighted average monthly 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 during the subsequent month.[9]

2.2 The performance of style-based strategies

I calculate both raw excess returns and factor-adjusted returns of the long-short portfolios using various benchmarks, including 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 the 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 diminishes to 273 under the five-factor model and further reduces 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, the result strongly suggests the pervasive nature of return predictability stemming from style categorization.[10]

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

[8] 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.

[9] 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.

[10] 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.

returns center around 0.60% and a large proportion of strategies are significant at the 1% level. The first two panels of Table 1 report the summary statistics of style strategies having a t-statistic of at least 1.96 in more detail. Panel A shows that, on average, the monthly return to the style-based long-short portfolios is 0.70%, and the overall performance ranges from 0.30% to 1.21%, depending on style and factor model specifications. Panel B reports the 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 distributions of t-statistics of extreme decile portfolios. I find that the magnitudes of t-statistics are generally larger than 2, suggesting that both the long side (the top decile portfolio) and the short side (the bottom decile portfolio) contribute to the return predictability.

Figure 5 shows the return distribution of style strategies by benchmark models, with outlier styles being marked.[11] Consistent with previous studies, I find that the style signal using the book-to-market ratio (BM) is a strong predictor for future stock returns. 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%.

Overall, while I confirm that BM is indeed a robust dimension for identifying styles, the results suggest that a comprehensive consideration of various firm characteristics beyond BM can enrich our insights into style-induced return predictability.

2.3 Profitability of characteristic-based and style-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. For instance, one might conclude that the importance of a characteristic in explaining expected returns determines the pricing effect of the derived style. While this conjecture lacks clear theoretical support, I address this matter empirically. Figure 6 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 analogous portfolios based on all 312 firm characteristics and compute

[11] I use the characteristic acronym as in Chen and Zimmermann (2021) in presenting style variables. The detailed description can be found in the *Signal Documentation* at `https://www.openassetpricing.com/data/`

value-weighted strategy returns from July 1963 to December 2021. Since many of the 312 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 (2021) and restricted to a subset of characteristics. In both cases, Figure 6 shows that the return of SS exhibits only a marginal relationship with the performance of CS, as evident from the close-to-zero slopes.

More specifically, in Table 2, I partition characteristics into two groups based on whether they significantly predict future returns in the extended sample (Panel A) or in the original sample (Panel B). Table 2 summarizes the conditional performance of SS. It is shown that the strength of the pricing effect of styles is nearly equivalent across these two groups. For instance, 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. In Panel B, I find similar patterns using the t-statistics reported in the original studies, which correspond to the in-sample predictive ability of characteristics.[12] Panel A of Table 2 also presents the number of CS with significant average returns. As previously reported, 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-based return predictability differs from the conventional characteristic-based model in its capacity to explain cross-sectional stock returns.

In sum, the profitability of style-based strategies exhibits little dependence on the predictive ability of the underlying characteristic. However, style investing suggests that characteristic returns and style returns would connect *intertemporally* in a dynamic way. That is, what matters is the time variation in the magnitude of characteristic returns. In subsequent analysis, I examine several determinants of style-based pricing effect.

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 evaluate how characteristic complexity

[12]The data on in-sample t-statistics is provided by Chen and Zimmermann (2021).

relates to style effects.

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 styles and the coordinated demand leads to excess comovement. As a result, the subsequent outperformance (underperformance) of stocks stems from the chasing (withdrawing) of high (low) past style returns. A testable prediction regarding comovements and returns of style portfolios can be derived from this channel. Specifically, higher comovement implies a higher probability of synchronized investing at the style level; consequently, the predictive ability of the style signal for future returns would be stronger.

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 the value $Comove_{BM,t}$. I conduct this calculation each month for each style, which generates a panel of comovements.

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 measure 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 be the participants engaging in style investing and generating market-wide impacts (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:

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

in which the dependent variable, $\Delta Inst_{i,q}$, is the quarterly change in stock i's institutional ownership.[13] The main independent variable $R_{i,q}^{style}$ 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.[14] Independent variables are lagged for one month relative to $\Delta Inst_{i,q}$.

Figure 7 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

[13] 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.

[14] 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.

level, I find that the average PIT is positive for most signals, with only one exceptions. 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). The result is also inconsistent with the alternative view that the predictive ability of style signals comes from price underreaction. Specifically, since firms within the same style group share similar fundamentals, the documented return predictability is potentially the consequence of the slow information dissemination among economically connected firms (e.g., Cohen and Frazzini (2008)). If underreaction is the primary driver of returns in style strategies, we should expect PIT to exhibit a *negative* relationship with future style returns. This is because value-relevant information would be incorporated more into the focal stock's price with increased PIT, thus mitigating mispricing.[15] 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 from styles stems from the style-level investing of institutions, rather than being attributed to underreaction arising from economic linkages.[16]

[15]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.

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

3.3 Retail trading and style strategy performance

While institutional investors play an important role in style investing, previous studies find that retail investors also adopt style-categorization in their investment decisions (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.[17] 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.[18]

Since the retail trading data is limited and the retail 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' 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

[17] 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/`

[18] 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.

of institutional trading ($\overline{PIT}_{style}$) of Section 3.1 and the average comovement ($\overline{Comove}_{style}$) of Section 3.2.

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 conclusions.

3.4 Characteristic attractiveness and style strategy returns

In Section 2.3, I have shown that the presence of the style-derived pricing effect does not rely on the predictive ability of the underlying characteristics. This is because the style investing model posits that investors are drawn to and extrapolate from transient price fluctuations that occur recently, rather than trading established stock return "anomalies." For example, when value stocks significantly outperform growth stocks, this category would attract investors' attention and induce more style-level trading. Similarly, when growth stocks substantially outperform value stocks, investors are also motivated to trade in that style direction. Both scenarios suggest enhanced price impact and thus style strategy performance. In other words, style investors pursue return trends without strong priors on the characteristic's predictive ability for future returns. 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 the characteristic return spread (CRS) for each style as the absolute value of the long-short strategy return associated with the underlying characteristic. For instance, CRS for the value style is calculated as the absolute value of the return difference between the top and bottom book-to-market ratio decile portfolios in the current month. 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 the 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 (i.e., the characteristic-based strategy return without taking absolute values) 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.[19]

In Panel B of Table 6, I examine the predictive ability of several alternative proxies. First, I use the original characteristic return instead of the absolute value. Consistent with my hypothesis, 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.[20] 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 spread between extreme characteristic deciles.

[19]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.

[20]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 (2021) database).

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).

3.5 Evaluating implementation complexity using ChatGPT

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.[21] 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.[22] Specifically, I obtain text-form detailed descriptions of each characteristic

[21]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.

[22]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).

from the OSAP website. The descriptions provided by Chen and Zimmermann (2021) 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 8 illustrates the prompt used in this section. To account for potential variability and randomness in ChatGPT's responses, I submit the same prompt independently for 100 rounds and calculate the average complexity score for each characteristic.[23]

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.[24] Economically, a one-unit increase in the complexity score corresponds to an approximately 0.21% reduction in the average style strategy return.

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

[23]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.

[24]The prompt depicted in Figure 8 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.

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 coefficient on complexity remains negative across all specifications.[25]

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 focused on high-tech firms would naturally involve investment in companies with comparable investment activities and valuation ratios. The complex interdependence between investment styles emphasizes the necessity of identifying style clusters within a high-dimensional space. In this section, I examine the correlation structure of styles through pairwise correlations and principal component analysis. Building upon the results, I investigate the role of dimensionality in unveiling the return predictability emanating from composite styles.

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 (2021), and Chen and McCoy (2022) document that the correlations between characteristics and portfolio returns are generally

[25]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.

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 I have shown that most characteristics-derived style signals generate significant predictive ability for stock returns, it is important to examine the interdependence of styles.

Figure 9 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 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 predictors and strategy returns are highly correlated. The pairwise correlations among style signals tend to cluster around 0.40, whereas those among strategy returns cluster around 0.60. Note that the interdependence of style returns should not be solely constrained by the correlations between characteristics. To illustrate this, consider two characteristics, denoted as x and y. They satisfy a stochastic quadratic relation: $y_{i,t} = a + bx_{i,t}^2 + \varepsilon_{i,t}$, with $Corr[x_{i,t}, y_{i,t}] = 0$. 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 zero.

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 the 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 20. 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 10 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 10 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 nearly equal contributions to the composition of PC1. Column 4 of Table

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

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 the 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 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, assume that there are 3 characteristics in total, (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, even a randomization approach is computationally intensive when dealing with the examination 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 the 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 which styles are incorporated in the construction process for a specific number of dimensions.

Figure 11 reports the performance of high-dimensional style strategies graphically. Similar to my baseline analysis, I form decile portfolios based on the style signal and calculate the average return to the long-short strategy. 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 (2022) and Kozak et al. (2020) that point to a high dimensionality feature of expected stock returns. However, my result is also considerably different from previous work. The standard implementation of machine learning methods in asset pricing involves estimating a function $g(\cdot)$ to capture conditional

[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.

expected returns (Gu et al., 2020):

$$\mathbb{E}_t(r_{i,t+1}) = g(\mathbf{z}_{i,t}), \tag{10}$$

where $\mathbf{z}_{i,t}$ is the vector of predictor variables associated with firm i and $r_{i,t+1}$ is stock return in the next period. When testing the return predictability from high-dimensional styles, as a comparison, the constructed predictor (i.e., the style signal) is *one-dimensional*, and predictive models are *not employed* during parameter estimation. Nevertheless, it becomes evident that higher dimensionality helps to uncover the predictable return pattern. From an economic perspective, the complexity of diverse style investment strategies makes it challenging to identify the equilibrium capital allocations, and hence the true cluster structure. Machine learning-based models have the potential to approximate the style representation of stocks with higher accuracy, thus unveiling return predictability.

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 cross-stock return predictability. This section seeks to reconcile what appears to be contradictory findings by constructing styles in the PC space rather than in the characteristic space. The intuition behind this is that, while investment styles are diverse and heterogeneous, characteristics exhibiting interdependence might lead to correlated capital allocation. For instance, 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, the 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 12 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 11, one sees that 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 although there is little redundancy among individual characteristics, the PC space exhibits a higher degree of sparsity. They find that a stochastic discount factor (SDF) constructed with 4 PCs performs quite well in describing portfolio returns based on 55 characteristics, whereas an SDF with 6 PCs achieves almost maximum out-of-sample R^2 from portfolios based on 80 financial ratios. In the context of style returns, Figure 11 indicates that a large number of characteristics is necessary to reveal the potential return predictability. Nevertheless, Figure 12 suggests that finding a sparse representation of styles that captures this pricing implication is feasible within the PC space.

The economic rationale of this finding lies in the close connection between comovements and expected returns. As demonstrated by Kozak et al. (2018), even in an economy where asset prices are affected by irrational beliefs and demand, the variation in cross-sectional expected returns should be explained by common factors of return covariances, as long as near-arbitrage opportunities are absent. In the model of style investing (Barberis and Shleifer, 2003), such common factors manifest as a consequence of investors trading assets at the style (characteristic) level and chasing style performance. In particular, the PCs of characteristics adeptly capture the clustering structure of the coordinated demand, with the returns of PC styles representing the sources of comovements.[28] As such, style returns derived from high-eigenvalue PCs of characteristics contribute substantially to the potential return predictability.

5 Additional tests

This section provides several additional tests. First, I test the implication of style investing in the context of market return predictability. Second, I assess the robustness of the main result of the paper, 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. Specifically, if the positive feedback trading at the style-level exerts pressure on asset prices, driving 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 the long-side return of the style strategy is extensively and persistently high, then I would expect a significant degree of continued overpricing attributed to style chasing. Similarly, if the short-side style return persistently remains low, then it signifies continued underpricing since the effective demand for low styles falls below the rational benchmark. That is, *both* the long- and short-side returns of style strategies should be *negatively* associated with future market trends. However, 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. Specifically, the price correction associated with the short-side mispricing 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 13 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:

$$Mkt_{t+1,t+h} = \alpha + \beta_1 \overline{R}_{long,t} + \beta_2 \overline{R}_{short,t} + Controls_t + \varepsilon_{t+1,t+h}, \tag{11}$$

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

[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.

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 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 have shown that comovement is a significant 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). It follows that the predictive ability of style signals is expected to be improved by removing the potential association with the short-term reversal effect.

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

[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.

the portfolio results using residual style signals. Consistent with my conjecture, the number of strategies with significant value-weighted returns increases and ranges 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 5 bps in general, with at least 85% of them committing statistical significance at the 1% level. Overall, I find that 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 based on value-weighted returns. 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 the style strategies earn positive returns with a t-statistics of at least 3, even after I put strict liquidity adjustments to the sample. Overall, I find that the pervasive predictive power of style signals is not sensitive to variations in portfolio construction and is not substantially affected by microcap issues.

5.4 Within- and cross-industry predictability

Trading based on industry classification is a prevalent strategy of style investing. 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. As industries are composite representations of individual characteristics, some styles might be contained in industry portfolios. As a result, the predictive ability of style signals is expected to be weaker once industry peers are removed. Similarly, if we identify styles with the restriction that style peers share the same industry classification, then

the return predictability would be stronger. This is because the within-industry construction is equivalent to augmenting an additional dimension in identifying styles, which I have shown in Section 4.2 that will enhance 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, there are more than half of the 312 styles still display a return predictability significant at the 5% level. In sum, while I confirm that styles based on characteristics are closely related to industry classifications, the associated return predictability is not likely to be completely ascribed 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. Nevertheless, I examine the result using a one-sort identification. Specifically, for each characteristic and at the end of each June, I sort stocks into ten groups based on the characteristic and calculate value-weighted average returns of other stocks in the same decile.

I also address the potential concern regarding data quality. While the Chen and Zimmermann (2021) database is one of the most comprehensive and becoming popular in empirical asset pricing studies, I supplement the test with two alternative datasets. The first one is the set of 53 characteristics (excluding size) used by Kozak (2020), and the second one is the set of 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 (2021) database.

Appendix Figure A3 shows that the main finding of this paper remains valid when using the single dimension in identifying styles. The 25th percentile of t-statistics is larger than 2, suggesting that we still have over 75% of style strategies that earn significant returns.

[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.

For the datasets of Kozak (2020) and Gu et al. (2020), the predictive power of style signals is even stronger as only two strategies in each dataset fail to generate significant returns. In addition, most style strategies earn positive profits and have a t-statistic higher than 3 in both databases. This heightened effectiveness might be attributed to the characteristics scrutinized by Kozak (2020) and Gu et al. (2020). It is possible that these characteristics have enjoyed widespread adoption in investment practice and attracted substantial attention from market participants. This alignment with characteristics relevant to style investing potentially contributes to the observed return predictability. As a comparison, many variables within the Chen and Zimmermann (2021) database may not directly factor into institutions' investment universe, 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 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 14 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:

$$X_{i,t} = \rho X_{i,t-1} + \epsilon_{i,t}, \tag{12}$$

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 (12). 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 14 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 systematically generate profitable style strategies.[32]

Collectively, these placebo tests provide evidence that the documented style-based return predictability are not artifacts of statistical noise or mechanical persistence in characteristics. The pervasive nature of style effects appears to be fundamentally driven by the price impact of style investing behavior among market participants.

6 Conclusion

The asset management industry has grown substantially in recent decades, giving rise to increasingly sophisticated and diverse investment styles. The style-level asset allocation in turn exerts notable impacts on equity pricing dynamics. Through an extensive analysis of 312 firm characteristics, I document a pervasive pattern of return predictability arising from style investing. Notably, over 80% of the style-based trading strategies generate statistically significant returns. Despite many characteristic-based anomalies losing their statistical significance in the extended sample, strategies based on styles maintain profitability.

The empirical findings align closely with the theoretical framework of Barberis and

[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.

Shleifer (2003). The return predictability is more pronounced for styles characterized by several key features: heightened comovement, intensified institutional trading, more retail investor participation, greater characteristic attractiveness, and low implementation complexity. These results would not have been attainable without the analysis of a large number of styles. This highlights the importance of high dimensionality in capturing the full spectrum of return predictability associated with style investing.

This research also offers insights into modeling expected stock returns. While traditional 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. The application of 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.

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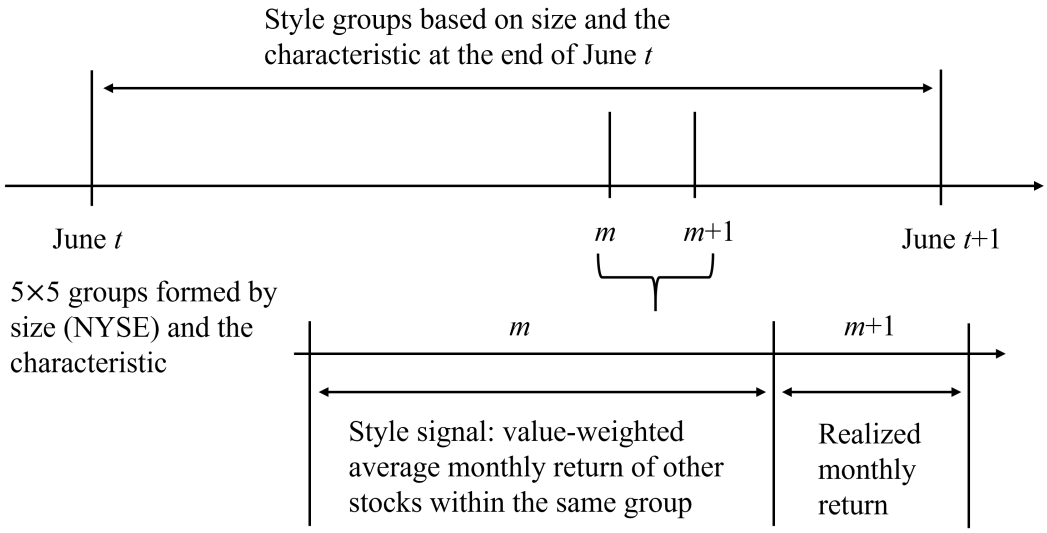


Figure 1. Timeline for signal construction and predictability tests.
This figure illustrates the timeline for constructing style signals and testing their ability to predict future stock returns. At the end of each June, style groups are defined by sorting stocks into 5×5 portfolios based on market capitalization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

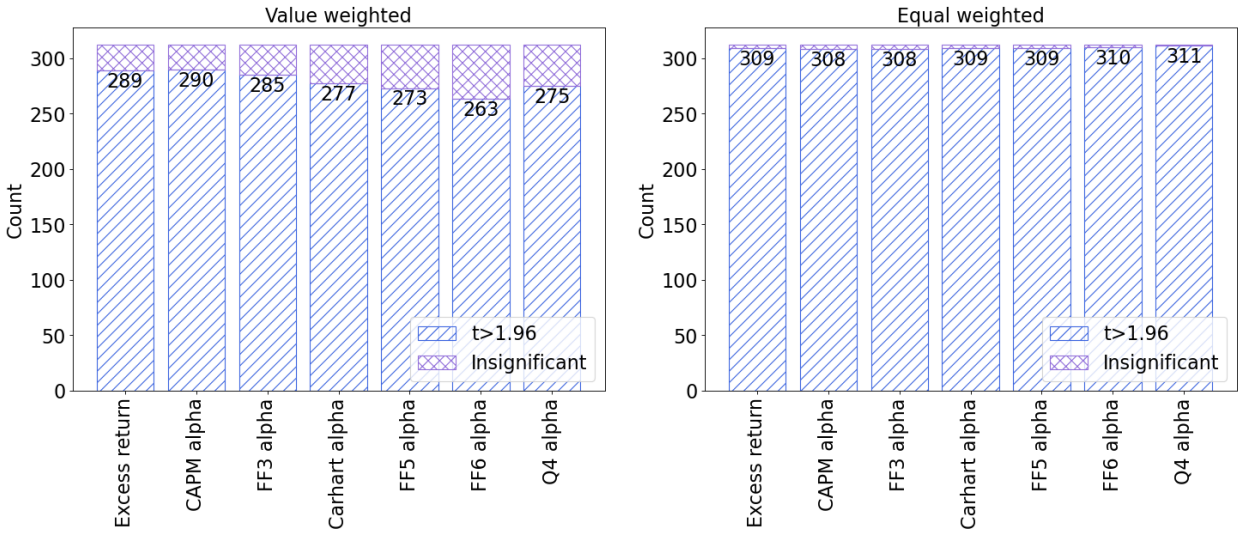


Figure 2. Summary of style strategy performance.
This figure reports the number of style strategies with significant mean returns ($t > 1.96$) and insignificant returns. For each style signal, I form decile portfolios each month with a one-month holding period and calculate value- and equal-weighted 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.

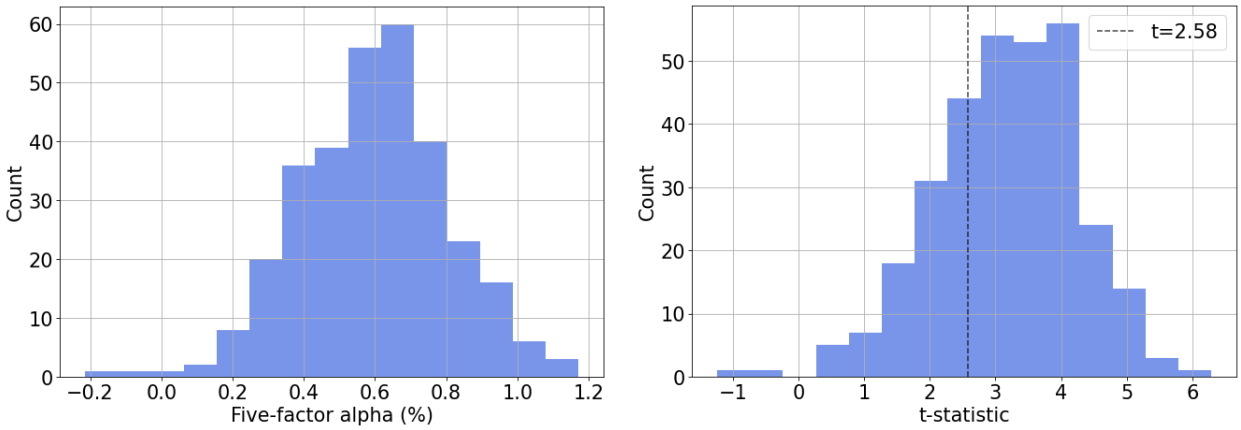


Figure 3. Performance distribution of style strategies.
This figure shows the distributions of returns (left) and t-statistics (right) of the 312 style strategies. Returns are adjusted based on the five-factor model of Fama and French (2015) and the t-statistics are calculated based on Newey-West adjusted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

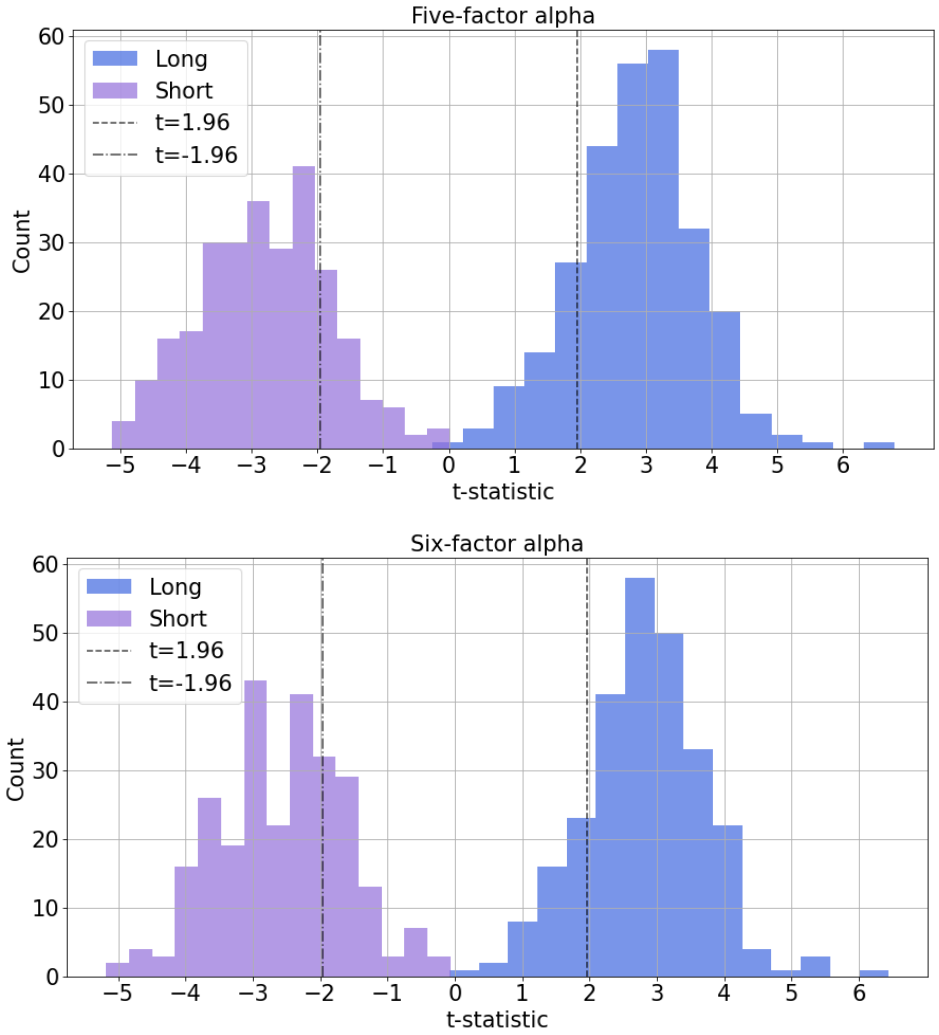


Figure 4. Long side and short side distributions of strategy t-statistics.
This figure shows the t-statistic distributions of the long and the short sides of style strategies. The sample is restricted to strategies with significant average returns. Returns are adjusted based on the five-factor model of Fama and French (2015) in the upper panel and the six-factor model (augmented with the momentum factor) in the bottom panel. The t-statistics are calculated based on Newey-West adjusted standard errors. The sample period is from July 1963 to December 2021.

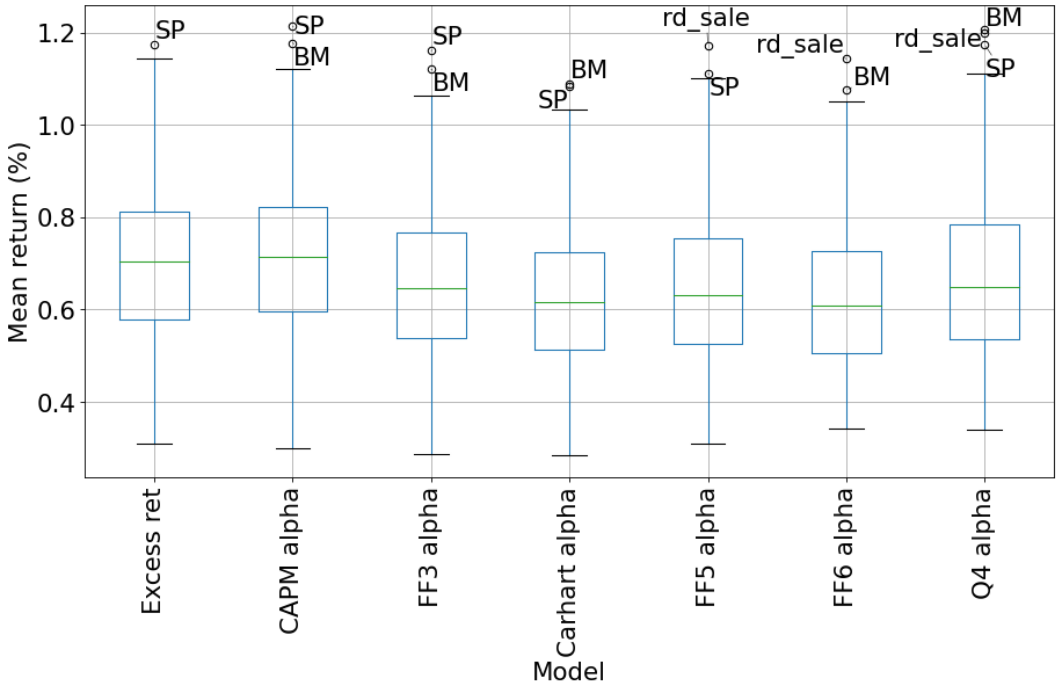


Figure 5. Style portfolio performance by asset pricing models.
This figure shows the performance of style strategies by benchmark models. The sample is restricted to strategies with significant average returns. The middle line is the median and the boxes are 25th and 75th percentiles. The whiskers extend 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).

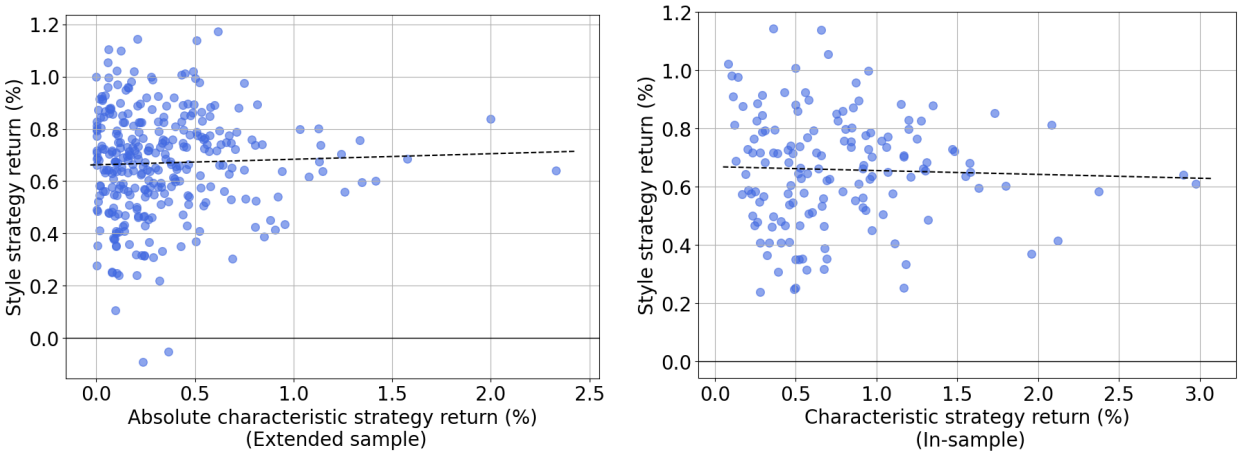


Figure 6. Mean returns of style-based and characteristic-based strategies.
This figure presents the scatter plots of style-based strategies (SS) and characteristic-based strategies (CS). The left panel includes all 312 characteristics and the absolute CS returns are calculated based on value-weighted 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.

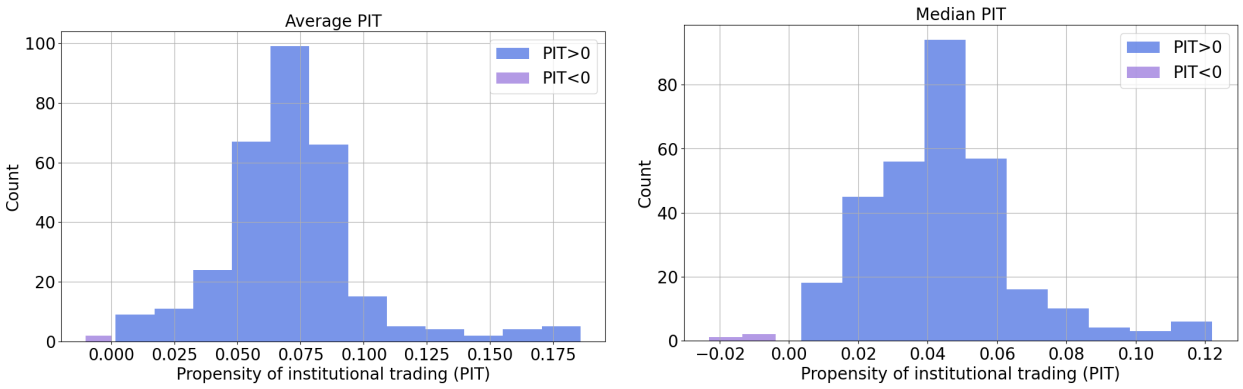


Figure 7. Distributions of estimated PIT.

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 8. 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.

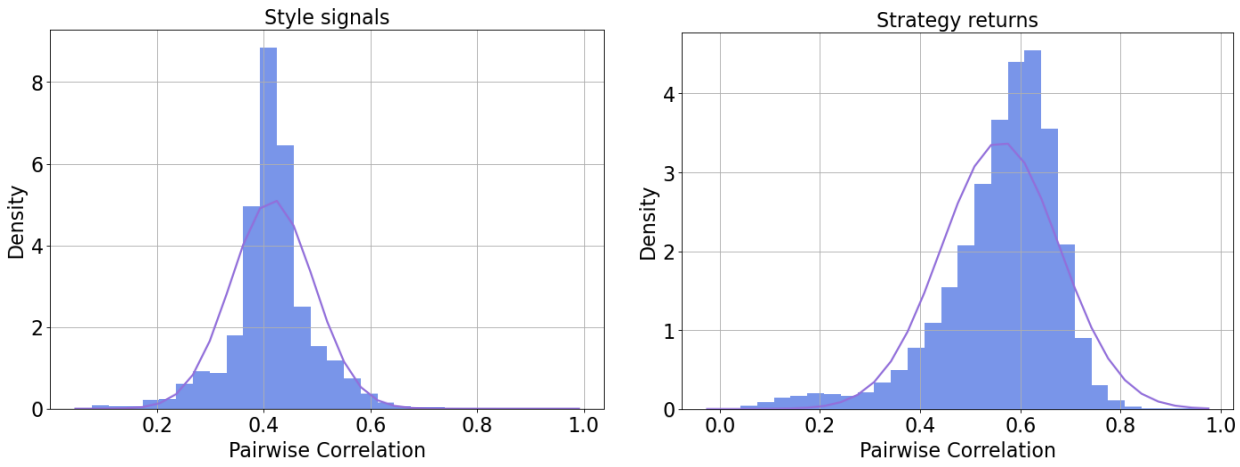


Figure 9. Correlations between styles.
This figure reports the distributions of pairwise correlations between style signals (style) and between style strategy returns. The sample period is from July 1963 to December 2021.

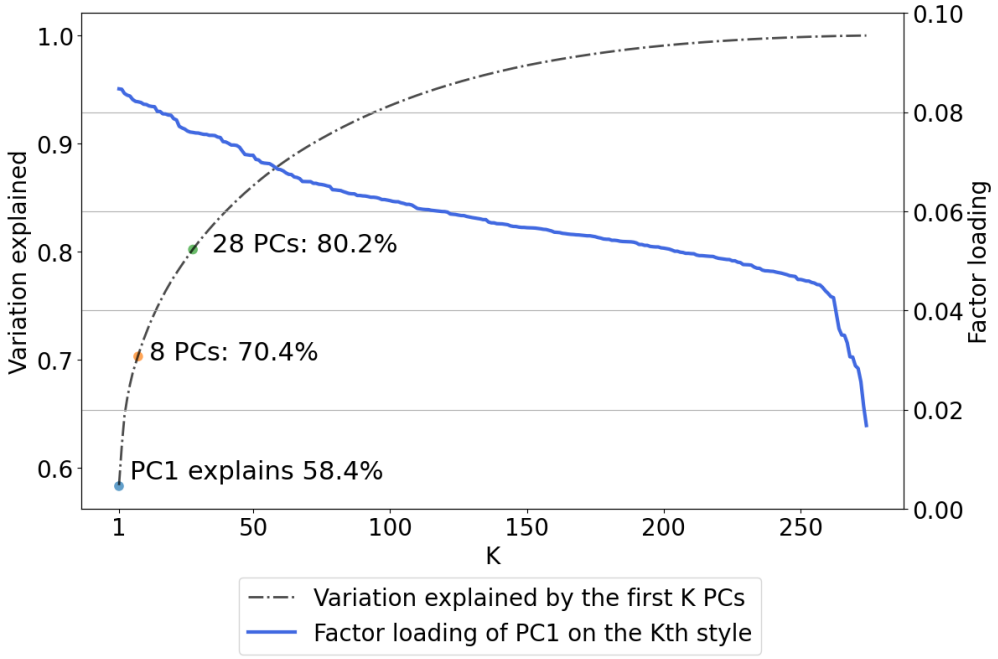


Figure 10. PCA of style strategies.

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.

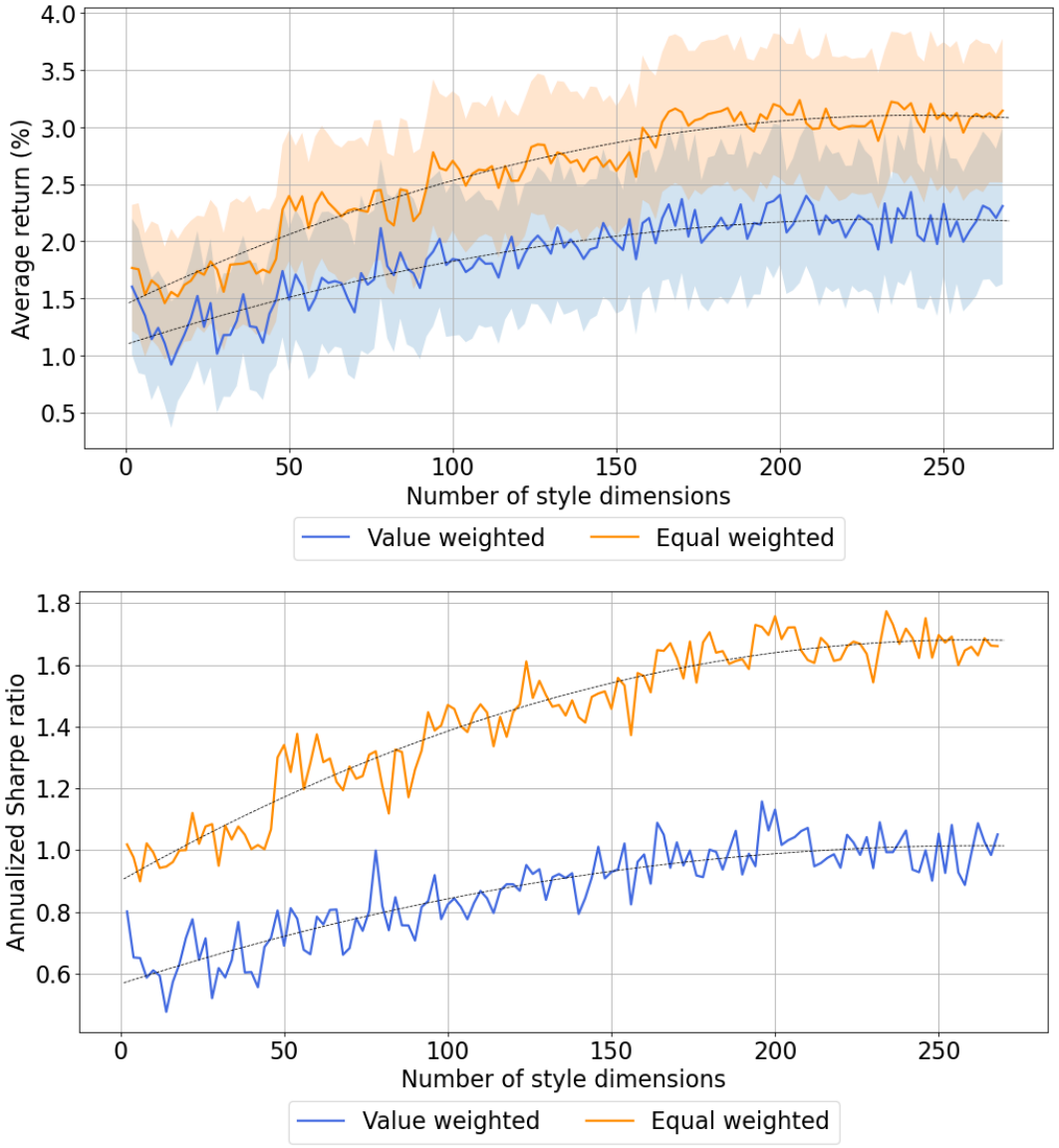


Figure 11. Style dimension and return predictability.
This figure plots the performance of style strategies as a function of the number of style dimensions. Each June, stocks are clustered into 50 groups based on d styles by k-means clustering. The style signal is the value-weighted average monthly return 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.

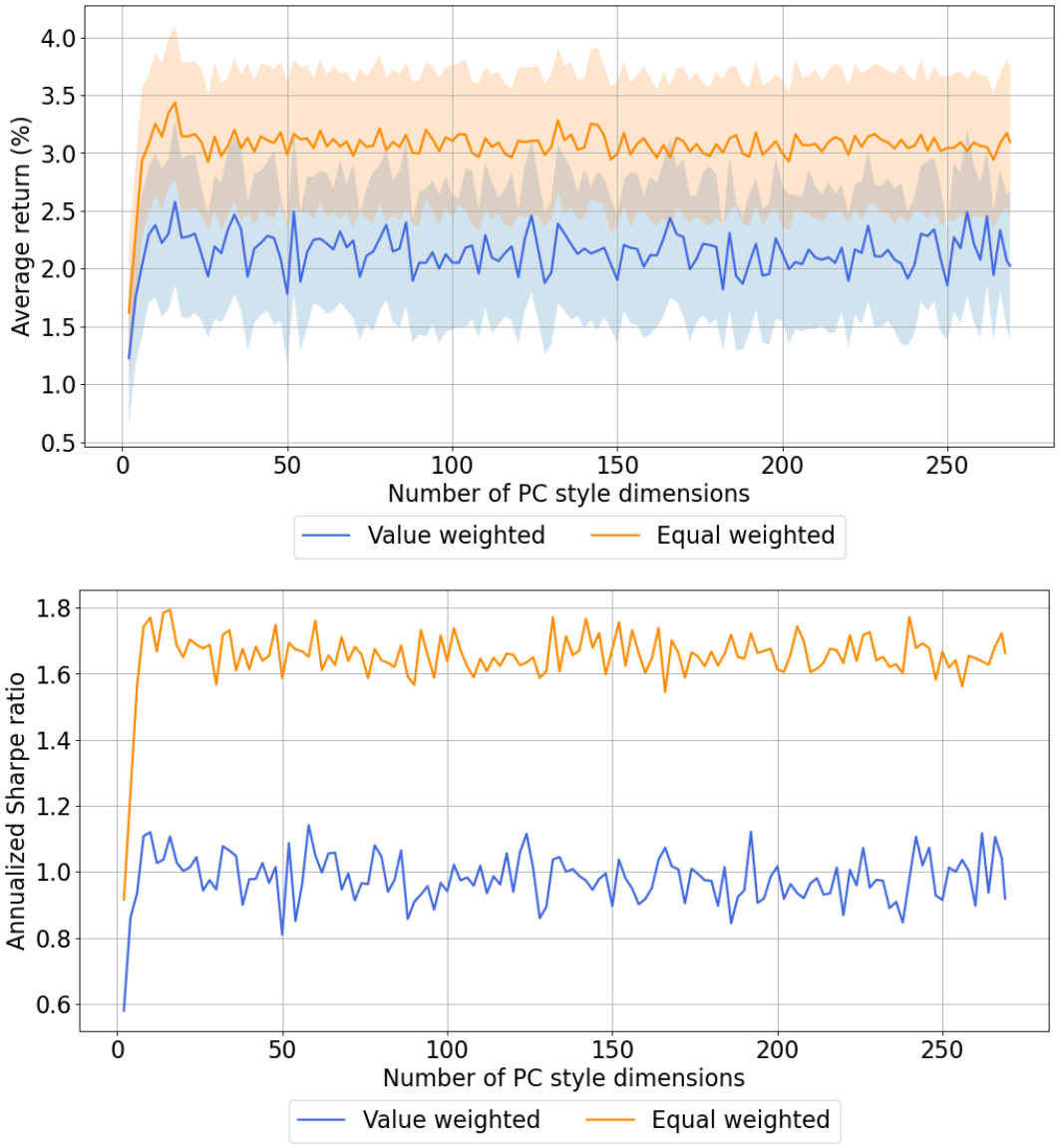


Figure 12. PC styles and return predictability.
This figure plots the performance of style strategies as a function of the number of PC style dimensions. Each June, I calculate the principal components (PCs) of characteristics and then catogorize stocks into 50 groups based on the first d PCs, using 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.

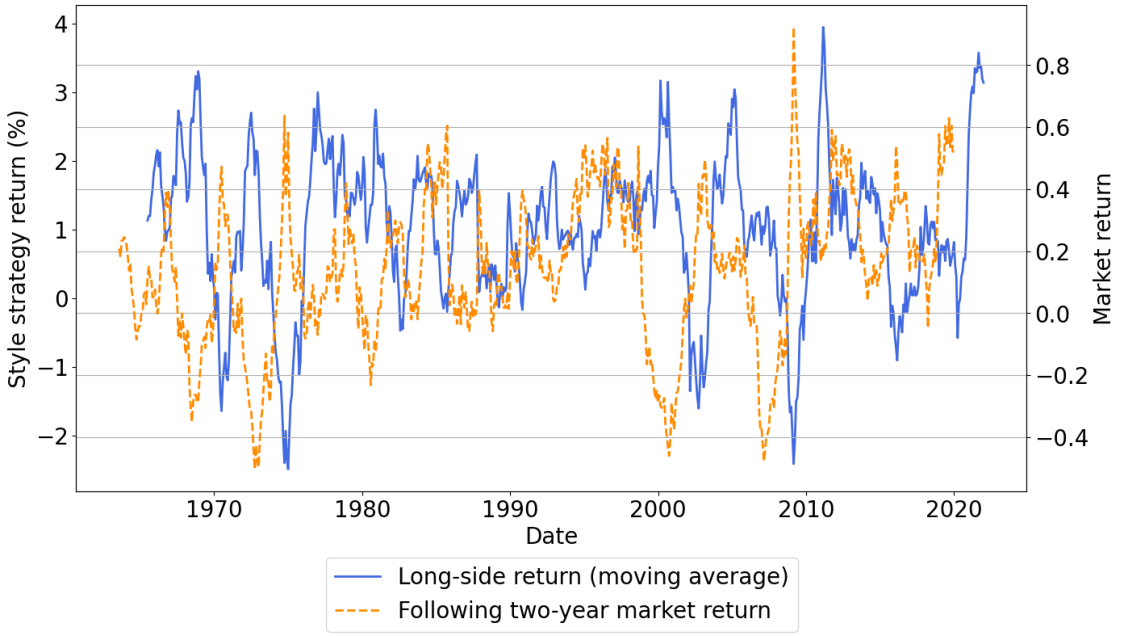
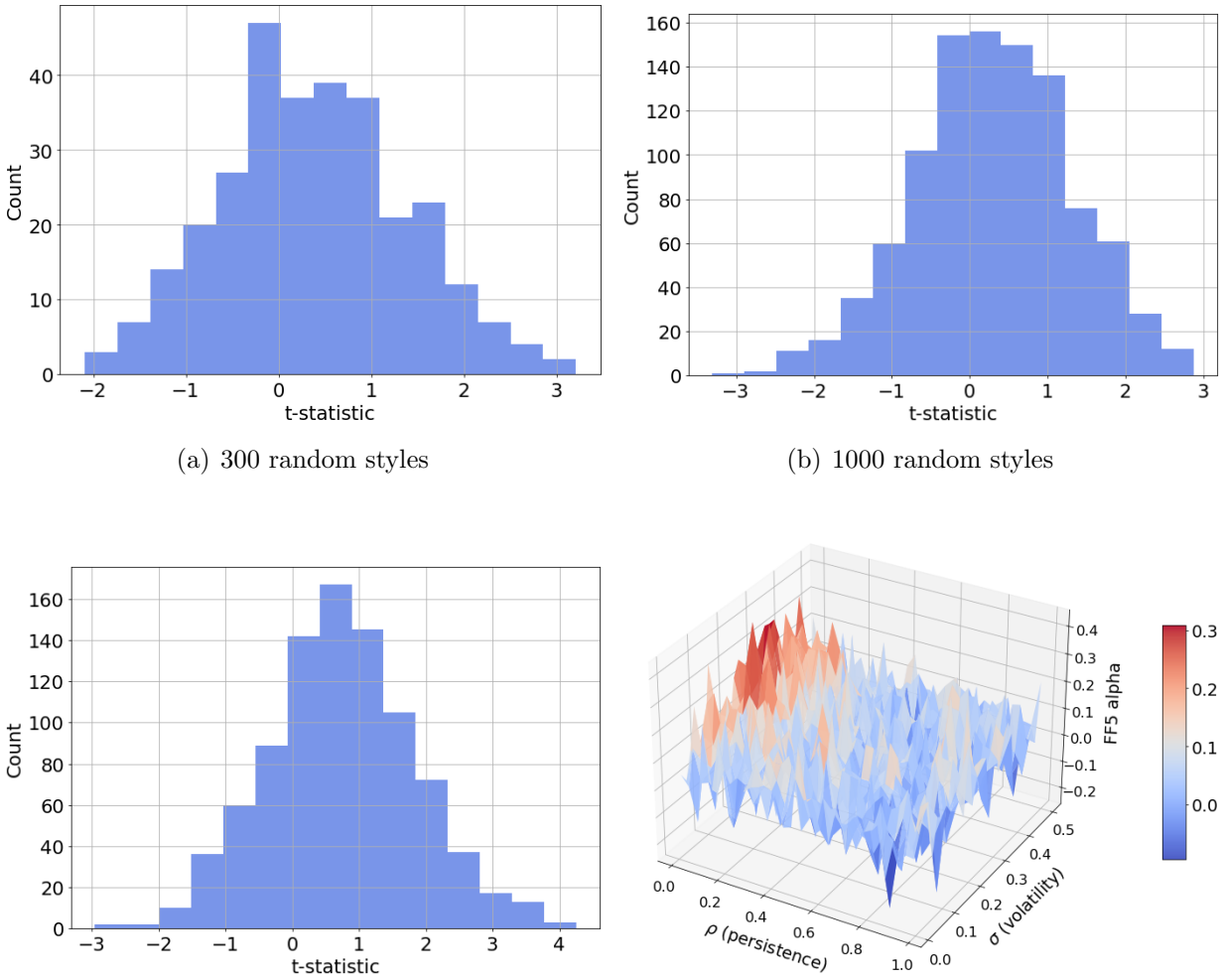


Figure 13. Style strategy returns and future market performance.
This figure plots the aggregate long-side style strategy returns and subsequent two-year cumulative market returns. To construct aggregate style strategy returns, I first calculate cross-sectional median returns of style strategies and 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 14. 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 (12). 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	Yes	No	Yes	Yes	No	Yes
Style FE	No	Yes	Yes	No	Yes	Yes
Two-way cluster	No	No	No	Yes	Yes	Yes
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	Yes	No	Yes	Yes	No	Yes
Style FE	No	Yes	Yes	No	Yes	Yes
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, 2021). 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	No	Yes	No	Yes	No	Yes
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	No	Yes	No	Yes	No	Yes
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	Yes	No	Yes	Yes	No	Yes
Style FE	No	Yes	Yes	No	Yes	Yes
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	Yes	Yes	Yes	Yes	Yes	Yes
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, 2021). 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	No	Yes	No	No	Yes
Data.Cat FE	No	No	Yes	No	Yes
Journal FE	No	No	No	Yes	Yes
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	Yes	Yes	Yes	Yes	Yes
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

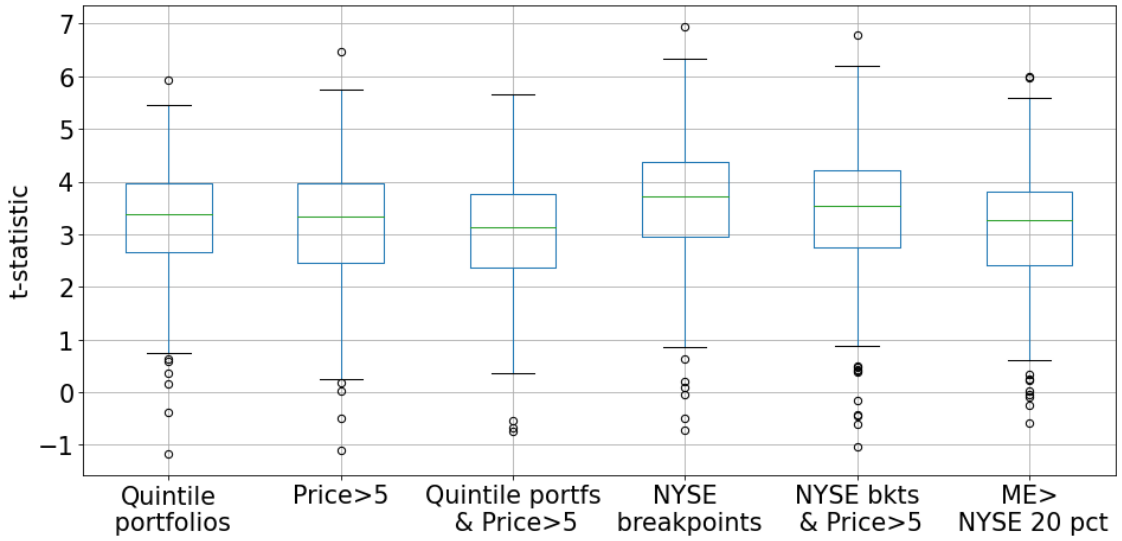


Figure A1. Style pricing under alternative portfolio specifications.
This figure plots the t-statistics of 312 style strategies under alternative portfolio specifications. The middle line is the median and the boxes are 25th and 75th percentiles. The whiskers extend to the smallest (largest) value within 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.

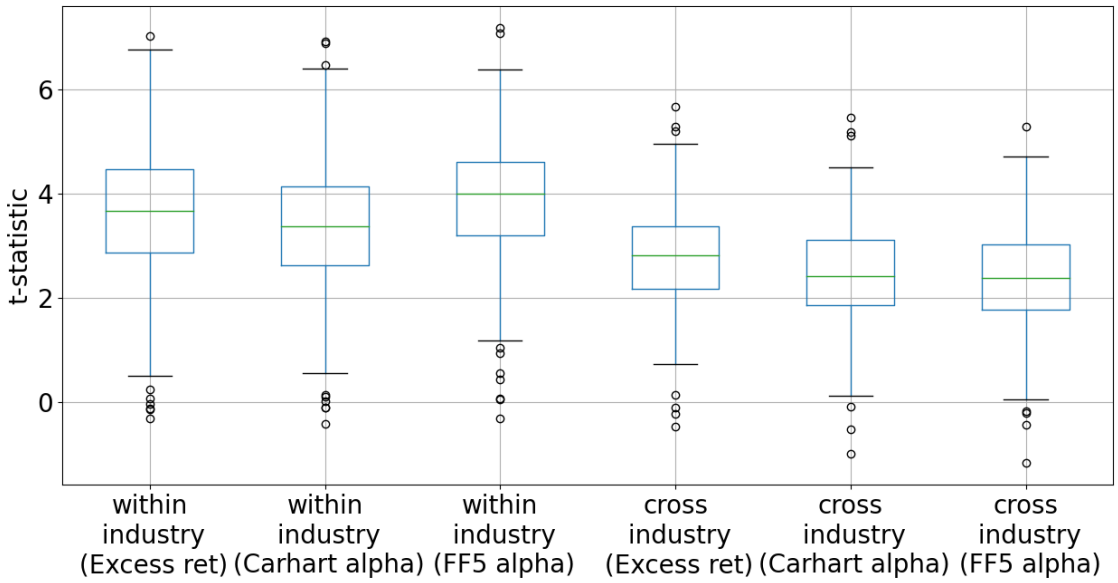


Figure A2. Within- and cross-industry style pricing.
This figure plots the t-statistics of 312 style strategies for which the return signals are calculated as value-weighted average returns of style peers within the same industry or in different industries. Industries are defined based on the 4-digit 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.

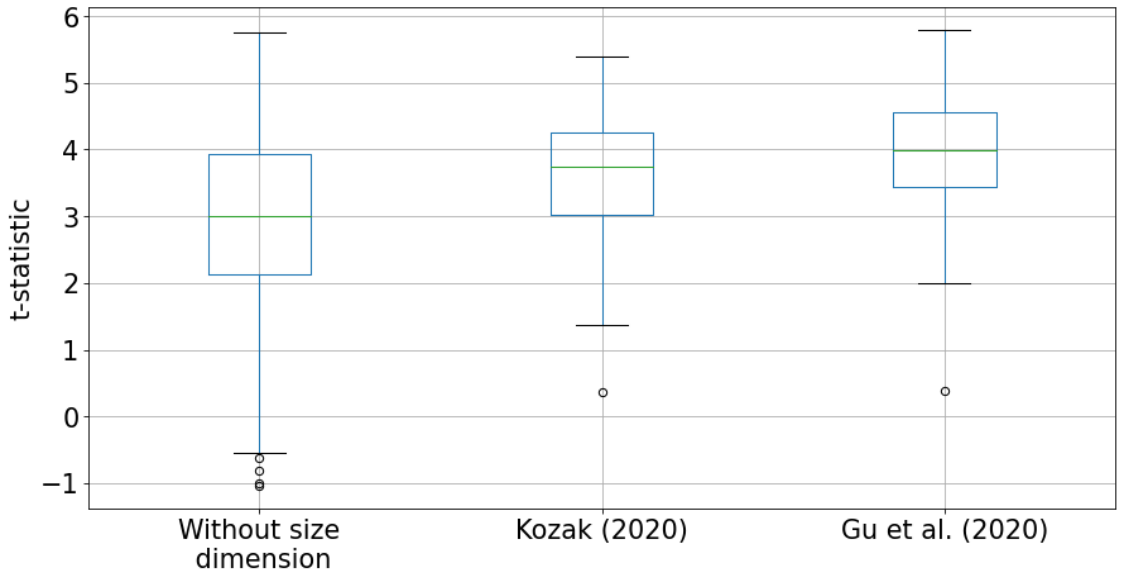


Figure A3. Style pricing under alternative style constructions and data sources. This figure plots the t-statistics of style strategies under alternative style constructions and characteristic datasets. The middle line is the median and the boxes are 25th and 75th percentiles. The whiskers extend to 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, 2021). 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	No	Yes	No	No	Yes
Data.Cat FE	No	No	Yes	No	Yes
Journal FE	No	No	No	Yes	Yes
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	No	Yes	No	No	Yes
Data.Cat FE	No	No	Yes	No	Yes
Journal FE	No	No	No	Yes	Yes
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