Style Switching and Asset Pricing *

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June 2024

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Abstract

This paper studies asset prices in a multi-asset economy where assets are actively managed in complex styles. When investors exhibit characteristics-based trading and extrapolative beliefs, asset demand switches between competing investment styles. Stocks sharing negative (positive) correlations within the characteristic space are categorized as dual (twin) styles and display cross-stock *reversal* (*momentum*). Trading strategies exploiting such predictability yield annualized returns of 12% from both reversals and momentum. Evidence from institutional trading supports the underlying mechanism. The framework further implies forecastable reversals and momentum in factor returns, which is confirmed in the data.

JEL classification: G11, G12, G14, G23

Keywords: Style investing, Asset demand, Reversal, Momentum, Factor predictability

*Preliminary, comments welcomed. I am grateful to Jianfeng Yu for his continuous guidance and encouragement. I am grateful to Xin Chen for sharing the Google Trends data. All errors are my own.

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1 Introduction

Style investing is prevalent in financial markets. Most funds are managed to invest in assets with specific themes, such as value stocks or high-tech companies, and target heterogeneous benchmarks. Despite its potential benefits to the asset management industry, however, style investing might in turn affect asset prices because of investors' inclination toward chasing performance (Barberis and Shleifer, 2003). By classifying stocks into predefined categories, many studies (e.g., Chen (2003); Barberis et al. (2005); Boyer (2011); Wahal and Yavuz (2013); and Hameed and Xie (2019)) document excessive within-category comovement and that past style returns (i.e., the average return of stocks within the same category) positively predict cross-sectional expected returns, probably because of the price pressure created by style chasing. This suggests that style investing seems to be responsible for asset pricing.

The pervasive adoption of style investing by active managers points to the importance of assessing its price impact. The within-category evidence, however, faces challenges in distinguishing between alternative interpretations, especially in a market with diverse styles and an increasing amount of passive ownership.[1] In this paper, I study a generalized characterization of style demand that incorporates complexity in asset characteristics. It naturally predicts the *switching* between competing styles: While the pursuit of "hot" styles leads to positive own-autocorrelations within categories, the externality of capital outflows induced by withdrawal from other styles generates *negative* cross-autocorrelations. This result is obtained without directly assuming investors wavering between categories. The framework provides an empirically implementable structure of competing styles, allowing me to examine the unique prediction of style investing (i.e., the negative spillover effect) in a nuanced way.[2]

My analysis builds on two concepts concerning asset demand and belief formation from recent developments in asset pricing literature. The first one is *characteristics-based trading* (Koijen and Yogo, 2019): investors' capital allocation depends on firm characteristics such as valuation, investment, and profitability. In the context of style investing, the loading of asset demand on some characteristic, determined by portfolio optimization, captures the preference for a specific style. The second one is *extrapolative belief* (Greenwood and Shleifer, 2014): expectations about future payoff depend on assets' past realized returns. I show that the

[1]These include, for example, the traditional positive feedback trading model (De Long et al., 1990), learning (Lewellen and Shanken, 2002), momentum trading (Hong and Stein, 1999), underreaction to fundamental news (Cohen and Frazzini, 2008; Ali and Hirshleifer, 2020), experience effect (Huang, 2019), attention spillovers (Chen et al., 2023), and passive index investing (Chabakauri and Rytchkov, 2021).

[2]The contrast and competitive relationship among styles is ambiguous ex ante, and ad-hoc empirical constructions (e.g., clustering through machine learning methods) often lack economic underpinnings. This issue is particularly pronounced when analyzing complex investment styles with high-dimensional features.

style demand of Barberis and Shleifer (2003) can be justified within this framework and that it generates additional testable predictions regarding cross-predictability in stock returns.

The intuition is as follows. When investors exhibit characteristics-based trading, the optimal portfolio weight is determined by the characteristics and (subjective) expected returns of all assets jointly. The propensity for investing in a specific characteristic depends on the average expected return associated with that dimension. The demand for any risky asset i, therefore, is described by the weighted average of expected returns across characteristic dimensions, where the asset's characteristic values represent the loadings on each dimension. Since the variation in characteristics is the only source of demand variation, assets exhibiting negative (positive) correlations in characteristics with asset i will receive negative (positive) weights. In the presence of extrapolative belief, this implies that the demand tends to decrease (increase) with respect to the past returns of assets sharing negatively (positively) correlated characteristics with i. In other words, investors *switch* between two competing styles, defined by the correlations among assets within the characteristic space.

I formalize this concept within an otherwise standard optimal portfolio choice model featuring characteristics-based trading and return extrapolation. In particular, the weight of an asset's past returns in the focal asset's demand is proportional to the inner product of their characteristic vectors. In cases where the characteristic space is one-dimensional and coarse (e.g., value versus growth), the demand function reduces to the classic form of Barberis and Shleifer (2003). For any stock i, I thus define *dual* (*twin*) styles by the stocks sharing negative (positive) inner products with i. In the model, investors tend to shift investments toward dual-style assets when these appear more attractive, and they finance this shift by selling focal stocks. Conversely, investors opt to invest in the focal stock to chase the performance of twin-style assets. Therefore, dual styles exhibit cross-stock reversals, whereas twin styles typically display cross-stock momentum.

In my empirical tests, I identify dual and twin styles by calculating cosine similarities along several dimensions, including value, profitability, investment, volatility, and momentum. The DUAL (TWIN) signal is calculated as the value-weighted average monthly return of stocks sharing negative (positive) cosine similarities with the focal stock. Consistent with my hypothesis, DUAL negatively predicts cross-sectional returns, whereas TWIN is positively associated with future returns. Specifically, when dual-style stocks perform relatively well, the focal stock tends to earn a lower subsequent return. In terms of economic magnitude, stocks in the top DUAL quintile underperform the bottom quintile by 100 basis points (bps) per month. In sharp contrast, the strategy of buying the top TWIN quintile and selling the bottom quintile earns a positive monthly return of 102 bps. These results are robust to controlling for prevailing asset pricing factors.

To ensure that the cross-predictability pattern is not driven by comovements with other known anomalies in the literature, I perform several Fama-MacBeth regressions to control for a battery of firm characteristics. In particular, previous studies document a strong industry momentum effect (Moskowitz and Grinblatt, 1999; Hou, 2007) and that the average returns of double-sorted portfolios based on size and book-to-market also predict cross-sectional returns (Lewellen, 2002; Wahal and Yavuz, 2013). Thus, I control for industry peer returns and the average return of size-value portfolio peers. I show that the predictive ability of DUAL and TWIN remains highly significant. Moreover, while being proposed from different economic mechanisms, Ali and Hirshleifer (2020) show that inter-firm linkages from shared analyst coverage can absorb most established lead-lag relations in the existing literature. Therefore, I also account for this effect in the regressions. Despite this control, however, I find that the returns of dual and twin styles still preserve strong predictive power.

The abnormal returns associated with dual and twin styles reflect the continued overreaction from style chasing. Specifically, the focal stock's price deviates downward from the fundamental value as the effective demand switches to dual styles, whereas the stock tends to be overpriced as investors chase the twin-style performance. Therefore, the strategy returns of DUAL and TWIN should eventually reverse in the long run. Indeed, the magnitude of returns for these two style strategies tends to increase within a one-year horizon and decline over longer horizons. The returns totally disappear and even reverse sign around 30 months after portfolio formation. This long-term reversal pattern also distinguishes style investing from alternative explanations such as information diffusion (Cohen and Frazzini, 2008) or the time-varying risk premium, under which the returns should be persistent rather than transient. In addition, the returns of style strategies display little sensitivity to macroeconomic conditions, suggesting that systematic risk or underreaction to common macro shocks is unlikely to be the main force driving my findings.

The key mechanism underlying the documented cross-stock return predictability, as mentioned earlier, is the switching of demand between dual and twin styles. To test this channel, I examine the variation in institutional trading (Edelen et al., 2016; McLean et al., 2020). Specifically, I regress quarterly changes in institutional ownership on the past dual- and twin-style returns. I find that an increase in dual (twin) returns implies a decrease (an increase) in institutional demand for the focal stock. The effect is similar when using the growth in the number of institutional holders to measure the variation in demand. This result supports the hypothesis that investors withdraw funds and switch to other stocks in the presence of high dual returns, whereas they continue to purchase the focal stock when the twin style performs well. Further analysis suggests that highly active institutions serve as the primary marginal investors, whose switching demand is responsible for style pricing. As a comparison, less active institutions exhibit little style demand. This finding is consistent with Koijen et al. (2023) that the demand of hedge funds and small-active investment advisors is more influential for expected returns.

I proceed to examine the trading of short sellers and retail investors, two important types of market participants who may also engage in style investing. As shown in Boehmer et al. (2008), most short sales are initiated by institutions. Consistent with my previous result, I find that the subsequent change in the short interest ratio is significantly higher (lower) for stocks with high DUAL (TWIN) compared to those with low DUAL (TWIN). Over short periods, this difference primarily arises from short sellers reducing their short positions in stocks with low dual-style returns and those with high twin-style returns. Additionally, short sellers gradually increase short interests in high-DUAL stocks within a one-year period, followed by a deceleration in trading activity over the long term. This pattern in short selling aligns with the long-term performance of style strategies. Retail investors also engage in style investing. Using retail trading volume data identified through the Boehmer et al. (2021) algorithm, I find that retail investors purchase focal stocks more when the twin-style return is high or when the dual-style return is low, although this behavior is more pronounced and significant only in the long run.[3] However, the evidence suggests that retail investors tend to act as style followers rather than marginal traders, as they retain purchases over longer horizons even if the style premium vanishes completely.

I conduct several additional tests to further validate the robustness of my findings. Using Bloomberg readership as a measure of institutional investor attention (Ben-Rephael et al., 2017), I find that the returns of DUAL and TWIN strategies are realized entirely following periods with high institutional attention. In contrast, retail investor attention, as measured by abnormal Google search volume (Da et al., 2011), does not exhibit any predictive ability for style effects. This result complements the evidence on institutional trading and highlights the role of professional traders' style-switching behavior in affecting asset prices. I also conduct a series of spanning regressions using alternative lead-lag effects that have been extensively studied in the literature. I find that the predictive ability of DUAL and TWIN remains significant after controlling for the potential correlations with other inter-firm linkages. I also examine the main predictability result using alternative specifications of dual and twin styles. It turns out that the style effect becomes stronger after purging out the short-term reversal

[3] Prior work indeed finds that retail investors' trading is highly persistent. See, for example, Barber et al. (2008); McLean et al. (2020); and Dong and Yang (2023).

effect; it is also robust to different parameter choices, the weighting scheme of style returns, or alternative combinations of characteristics used in constructing styles. I further conduct a placebo test by defining styles based on stock return correlations rather than characteristics correlations. The resulting style returns do not exhibit significant predictive ability for future returns.

Lastly, I extend my analysis to the predictability of factor returns. Consider two strategies (factors): Strategy A is a value investment that buys value stocks and sells growth stocks; Strategy B focuses on profitability by buying high-profitability stocks and selling low-profitability ones. Style investing implies that the demand for value (profit) stocks tends to increase in the presence of high recent returns of value (profit) stocks, which generates factor momentum in A and B, a pattern extensively studied in the recent literature (e.g., Gupta and Kelly (2019); Ehsani and Linnainmaa (2022); and Arnott et al. (2023)). More importantly, however, the switching feature of style demand suggests that cross-factor autocorrelations should also exist. Specifically, to the extent that the book-to-market ratio and operating profits are negatively correlated, a shift toward value investment is accompanied by withdrawal from the profitability strategy, thus generating cross-correlations in factor returns. The switching of factor demand holds generally even if the investor does not explicitly trade on these factors, as style investing implies that the asset demand is a linear function of past returns. That is, what matters is the correlations between characteristics within the asset space.[4] Using data on a large set of firm characteristics, I define dual (twin) factors as strategies sharing negative (positive) correlations in their underlying characteristics. Consistent with my conjecture, there exist strong cross-reversals for dual factors and a cross-momentum for twin factors. These findings underscore the potentially multi-layered impact of style switching on asset pricing.

Related literature. The seminal work by Barberis and Shleifer (2003) demonstrates the importance of style investing in affecting asset prices. Follow-up studies provide evidence on style-level investment behavior by institutional investors (Froot and Teo, 2008; Choi and Sias, 2009; Broman, 2022), retail investors (Kumar, 2009; Jame and Tong, 2014), active mutual funds (Teo and Woo, 2004; Wermers, 2012; Frijns et al., 2016), and hedge funds (Schauten et al., 2015). Regarding asset pricing implications, extensive research has documented that (1) stocks within the same category exhibit excessive comovement (Barberis et al., 2005; Greenwood, 2008; Green and Hwang, 2009; Boyer, 2011; Hameed and Xie, 2019) and (2) past style returns positively predict future stock returns (Chen, 2003; Wahal and Yavuz,

[4] As a comparison, recall that the asset-level style switching depends on the correlations between assets within the characteristic space.

2013; Chou et al., 2019). My work introduces a simple generalization of the style demand, through which styles can be explicitly and granularly represented by correlations among assets within the characteristic space. Empirically, I find evidence on both cross-stock reversals and cross-stock momentum, whereas prior studies have predominantly concentrated on the momentum aspect. I also investigate the style-switching propensity of different types of institutions, as well as short sellers and retail investors. This complements existing evidence on the style investing behavior of various market participants.

This paper is also related to the literature on the influence of demand shocks and asset management. Previous studies suggest that flow-induced transactions can generate large price pressure and lead to excess comovement (Greenwood and Thesmar, 2011; Vayanos and Woolley, 2013; Anton and Polk, 2014) and return predictability (Coval and Stafford, 2007; Lou, 2012; Vayanos and Woolley, 2013; Ben-David et al., 2022). More recent work focuses on the market impact of correlated demand shocks and benchmarking (Basak and Pavlova, 2013; Koch et al., 2016; Kim, 2022; Buffa and Hodor, 2023; Kashyap et al., 2023; Pavlova and Sikorskaya, 2023).[5] In addition, institutional trading also affects anomaly returns such as value and momentum (Ben-David et al., 2021; Chen et al., 2022; Peng and Wang, 2023). This paper expands the existing literature by delving into the asset pricing implications of style investing, a well-established and widely utilized strategy within the asset management industry. My findings suggest that the style-switching demand can generate considerable impacts on the return autocorrelation structure in a multiple-asset economy. The return predictability result also aligns with the findings of Brunnermeier and Nagel (2004), Griffin et al. (2011), and Edelen et al. (2016) that institutional investors' demand could amplify mispricing.

More generally, this paper also contributes to the fast-growing literature on the lead-lag effect in stock returns. This field has uncovered numerous inter-stock connections and corresponding cross-stock momentum effects. Researchers have delineated two primary explanations for these phenomena. The first explores underreaction-induced sluggish information diffusion, starting with the early work by Moskowitz and Grinblatt (1999), Hou (2007), and Cohen and Frazzini (2008).[6] The other branch proposes that retail investors' continued overreaction-driven excess demand also leads to positive cross-predictability.

[5] In a broader context, these studies are relevant to the research agenda of demand-based asset pricing. Koijen and Yogo (2019) propose a structural approach to estimate demand elasticities and evaluate the role of demand on asset prices. See also Gabaix and Koijen (2021) for a recent review.

[6] This includes, for instance, industry connections (Moskowitz and Grinblatt, 1999; Hou, 2007; Hoberg and Phillips, 2018), supply chains (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), conglomerate firms (Cohen and Lou, 2012), technological links (Lee et al., 2019), geographic links (Parsons et al., 2020), and shared analyst coverage (Ali and Hirshleifer, 2020).

Notable examples include stocks with similar characteristics (He et al., 2023) or adjacent listing codes (Chen et al., 2023). Distinct from these studies, style investing emphasizes the *coexistence* of cross-reversals and cross-momentum, which I confirm in the data. Moreover, the pricing effect of dual and twin styles remains robust even after controlling for a large number of inter-firm linkages. This suggests that style investing captures a novel dimension in explaining cross-sectional stock returns.

Finally, this paper also contributes to recent work on factor momentum (Lewellen, 2002; Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023; Yan and Yu, 2023). My findings suggest style investing as a potential explanation for the predictability pattern in factor returns. This paper also expands this field of research by showing an intertemporal reversal effect across various factors. However, it is worth noting that the evidence thus far is silent on the causal role of style investing in generating factor momentum. The factor-level return predictability might be partially attributed to statistical correlations in strategy constructions. A rigorous examination would require more granular transaction-level data or exogenous shocks to the adoption of style investing, which are far beyond the scope of this paper.[7] Nevertheless, the cross-factor reversals and momentum serve as a supplement to the asset-level result and illuminate possibilities for future research in this area.

The rest of the paper is structured as follows. Section 2 provides a conceptual framework of style investing and derives the style-switching demand. Section 3 describes the empirical construction of dual and twin styles. Section 4 presents the main empirical results on the asset pricing implications of style switching and examines the trading behavior of market participants. Section 5 provides additional robustness tests. An extension to factor return predictability is presented in Section 6. I conclude in Section 7.

2 Conceptual framework

In this section, I formalize the intuition behind style switching using a simple portfolio choice model. The model features two key elements: (1) the asset demand is represented at the characteristics level (Koijen and Yogo, 2019), and (2) the belief about future returns is extrapolative (Barberis et al., 2018). Under this setting, I show that the style demand function of Barberis and Shleifer (2003) can be nested in this general yet simple framework. That is, instead of directly assuming that investors compare style performance to decide fund allocations, the framework generates the switching of asset demand endogenously as a result of

[7] For example, Ben-David et al. (2021, 2022) find that a June 2002 reform in Morningstar's mutual fund rating methodology generates substantial impacts on style-level demand and profitability of factors.

characteristics-based trading and return extrapolation. Importantly, it also provides guidance on empirically constructing competing styles between which investors switch funds. Negative (positive) cross-correlation in stock returns occurs as a result of investors extrapolating and chasing the past performance of stocks in dual (twin) styles.

2.1 Assets and style extrapolators

Consider an economy with one risk-free asset and N risky assets. The return of the risk-free asset is normalized to zero, and each share of risky asset i is a claim to a liquidating dividend $D_{i,T}$ to be paid at the final date T:

$$D_{i,t} = D_{i,0} + \sum_{t=1}^{T} \varepsilon_{i,t}, \tag{1}$$

where $\varepsilon_{i,t} \sim N(0, \sigma^2_{i,\varepsilon})$, i.i.d. over time. To shut down the channel of commonality in cash-flow shocks, I restrict attention to a simple covariance structure where $cov(\varepsilon_{i,t}, \varepsilon_{j,t}) = 0$ for any $i \neq j$. Therefore, the covariance matrix of idiosyncratic cash-flow shocks, denoted as $\mathbf{\Gamma}$, is a diagonal matrix $diag(\sigma^2_{1,\varepsilon}, ..., \sigma^2_{N,\varepsilon})$. This is designated to highlight the role of pure demand shocks in driving cross-correlation in returns. The price of risky asset i at time t is denoted by $P_{i,t}$. Throughout the following analysis, I refer to the price change, $P_{i,t} - P_{i,t-1}$, as asset i's return at time t.

The trader making investment decisions in this economy is referred to as the style extrapolator. Specifically, the style extrapolator seeks to maximize a constant absolute risk aversion (CARA) utility, defined over the next period's wealth, by choosing a portfolio $\mathbf{L}^X_t = (L^X_{1,t}, ..., L^X_{N,t})'$ based on the current wealth (W_t). The term $L^X_{i,t}$ is the amount of capital allocated to asset i. The optimal portfolio choice problem is given by

$$\max_{\mathbf{L}^X_t} \mathbb{E}^X_t[-e^{-\gamma(W_t + (\mathbf{P}_{t+1} - \mathbf{P}_t)'\mathbf{L}^X_t)}], \tag{2}$$

where γ is the risk aversion parameter and $\mathbf{P}_t = (P_{1,t}, ..., P_{N,t})'$ is the price vector. In particular, the trader invests in risky assets based on asset characteristics and has extrapolative expectations, as modeled below.

Assumption 2.1. ***Characteristics-based trading.*** *The demand of style extrapolators for asset i is an affine function of K firm characteristics:*

$$L^X_{i,t} = \mathbf{\Omega}'_t C_i,$$

where the demand loading vector $\mathbf{\Omega}_t = (\omega_{1,t}, ..., \omega_{K,t})'$ *is constant across assets and* $C_i = (c_i^1, ..., c_i^K)'$ *is a vector of characteristics of firm* i*.*

Assumption 2.2. ***Return extrapolation.*** *Style extrapolators form expectations of future returns by extrapolating past price changes:*

$$\mathbb{E}_t^X(P_{i,t+1} - P_{i,t}) = (1-\theta)\sum_{l=1}^{t-1}\theta^{l-1}(P_{i,t-l} - P_{i,t-l-1}) + \theta^{t-1}X_1,$$

where $\theta \in (0,1)$ *is a constant measuring the degree of extrapolation and* X_1 *denotes the initial extrapolator enthusiasm.*

A crucial property of $\mathbf{\Omega}_t$ is that, for each characteristic k, $\omega_{k,t}$ is constant across assets. This captures the core of style investing in the sense that the trader allocates funds at the style level. Therefore, variation in characteristics is the only source of the variation in demand. In the context of style investing, the demand loading on a characteristic captures the preference for this specific style. For example, let BM and MOM denote the book-to-market ratio and momentum, respectively. Then, $\omega_{BM,t} > 0$ indicates a value trader, as the investor tends to buy stocks with high book-to-market ratios. Similarly, $\omega_{MOM,t} < 0$ signifies a contrarian trader.

In this paper, I refrain from distinguishing between different mechanisms behind characteristics-based trading. For example, this demand could simply reflect a fund manager's investment strategy or stem from limited attention (Peng and Xiong, 2006). Given the focus on the asset pricing implications of style investing, a more detailed decomposition of this demand is not pursued in this study. Koijen and Yogo (2019) demonstrate that characteristics-based demand matches institutional and household holdings well. As such, I consider this form of asset demand as an established factor without delving into intricate psychological or institutional underpinnings. It will be straightforward to show that, under this assumption, the direction and magnitude of demand loading on characteristics are determined by the investor's subjective expectation along each dimension. As a result, introducing extrapolative beliefs naturally gives rise to a demand function with a propensity for style switching.

Over-extrapolation has been proven to be an important psychological mechanism underlying many financial market anomalies. Greenwood and Shleifer (2014) find that extrapolation bias exists pervasively across six sources of survey expectations, such as individual investors and CFOs. Extensive evidence suggests that security analysts, firm managers, fund managers, and professional forecasters generally exhibit extrapolative belief (La Porta, 1996; Gennaioli et al., 2016; Angeletos et al., 2021; Deng, 2021; Andonov and

Rauh, 2022; Barahona et al., 2023). More recently, Bybee (2023) shows that extrapolative expectation even applies to forecasts generated by large language models such as ChatGPT. I follow prior studies and employ a geometric decay model to represent return extrapolation. In particular, there is a one-period lag between belief formation and past price changes, as in Barberis et al. (2018) and Liao et al. (2022). This modeling choice captures the notion that style investors allocate funds by comparing the *past*, not the current, performance of assets.[8]

2.2 Derivation of style demand

Let $\Theta = (C_1, ..., C_N)'$ be an $N \times K$ matrix of characteristics, where row i represents the characteristic vector of asset i and column k is the vector of characteristic k of all assets. The first-order condition of problem (2) gives the optimal demand function:

$$\mathbf{L}_t^X = \frac{1}{\gamma}\mathbf{\Gamma}^{-1}\mathbb{E}_t[\mathbf{P}_{t+1} - \mathbf{P}_t] = \Theta\mathbf{\Omega}_t, \tag{3}$$

where it is assumed that the investor perceives the covariance matrix of cash-flow shocks as the covariance matrix of price changes (e.g., Barberis et al. (2018)). Consequently, the characteristic loading of the demand function is given by

$$\mathbf{\Omega}_t = \frac{1}{\gamma}(\Theta'\Theta)^{-1}\Theta'\mathbf{\Gamma}^{-1}\mathbb{E}_t^X[\mathbf{P}_{t+1} - \mathbf{P}_t]. \tag{4}$$

That is, the propensity for investing in a specific style depends on the subjective evaluation of payoffs along that dimension (i.e., $\sum_{i=1}^N c_i^k \mathbb{E}_t^X(P_{i,t+1} - P_{i,t})/\sigma_{i,\varepsilon}^2$).[9] Consequently, the demand function is given by

$$\mathbf{L}_t^X = \frac{1}{\gamma}\Theta(\Theta'\Theta)^{-1}\Theta'\mathbf{\Gamma}^{-1}\mathbb{E}_t^X[\mathbf{P}_{t+1} - \mathbf{P}_t]. \tag{5}$$

This implies that, when deciding the amount of capital allocation for a particular asset, the trader takes into account the joint distribution of characteristics of all assets. It follows that

[8] The one-period lag setting is adopted in this paper primarily to align with the approach of Barberis and Shleifer (2003) and facilitate a convenient comparison of the derived style demand function. However, the style-switching demand is unaffected by assuming away this one-period lag in belief formation. Extrapolative belief without lags appears more consistent with empirical evidence and is also employed in related studies such as Barberis et al. (2015) and Pan et al. (2021).

[9] Also note that $\mathbf{\Omega}_t$ can be interpreted as the ordinary least squares (OLS) estimate from a linear regression of asset payoffs on characteristics. Thus, the derivation of $\mathbf{\Omega}_t$ can also be viewed as the investor minimizing her forecast errors by employing a linear model of asset characteristics, despite the belief being biased as a result of over-extrapolation.

the demand for any risky asset i can be written as

$$L_{i,t}^X = \frac{1}{\gamma}\sum_{j=1}^{N} C_i'(\Theta'\Theta)^{-1}C_j \frac{\mathbb{E}_t^X(P_{j,t+1} - P_{j,t})}{\sigma_{j,\varepsilon}^2}. \tag{6}$$

Therefore, we can define asset-specific styles based on the signs of inner products between assets in the characteristic space. Specifically, for any risky asset i, the *dual* style is defined as the set of asset p with a negative correlation in terms of characteristics, i.e., $C_i(\Theta'\Theta)^{-1}C_p < 0$; the *twin* style is defined as the set of asset q with a positive correlation, that is, $C_i'(\Theta'\Theta)^{-1}C_q > 0$. The style demand is hence represented by

$$\begin{aligned} L_{i,t}^X = & \underbrace{\frac{1}{\gamma}\sum_{\{p|C_i'(\Theta'\Theta)^{-1}C_p<0\}} C_i'(\Theta'\Theta)^{-1}C_p \frac{\mathbb{E}_t^X(P_{p,t+1} - P_{p,t})}{\sigma_{p,\varepsilon}^2}}_{\textit{Dual styles}} \\ & + \underbrace{\frac{1}{\gamma}\sum_{\{q|C_i'(\Theta'\Theta)^{-1}C_q>0\}} C_i'(\Theta'\Theta)^{-1}C_q \frac{\mathbb{E}_t^X(P_{q,t+1} - P_{q,t})}{\sigma_{q,\varepsilon}^2}}_{\textit{Twin styles}} \end{aligned} \tag{7}$$

Barberis and Shleifer (2003) consider an economy with two categorical styles that form a partition of risky assets; that is, each risky asset is exclusively assigned to one of these two styles. The style demand implies that investors allocate funds at the style level, and the amount allocated to each style is determined by comparing the relative past performance between styles.[10] To see how the style demand function of Barberis and Shleifer (2003) can be derived, consider the case where there are two styles, $Value$ and $Growth$, spanning the market. Now define a one-dimensional characteristic c_i, such that $c_i = 1$ if $i \in Value$ and $c_i = -1$ if $i \in Growth$. Let i be a value stock; then equation (7) reduces to

$$L_{i,t}^X = \frac{1}{\gamma N}\left(\sum_{p\in Value} \frac{\mathbb{E}_t^X(P_{p,t+1} - P_{p,t})}{\sigma_{p,\varepsilon}^2} - \sum_{q\in Growth} \frac{\mathbb{E}_t^X(P_{q,t+1} - P_{q,t})}{\sigma_{q,\varepsilon}^2}\right). \tag{8}$$

That is, the trader's time t allocation to value stocks depends on the value style's past performance (captured by the extrapolative belief $\mathbb{E}^X$) *relative to* that of the growth style.[11]

[10] Details of the corresponding demand function can be found in equations (9) and (10) of Barberis and Shleifer (2003).

[11] Barberis and Shleifer (2003) also set a constant term in the style demand function, referred to as the "average long-run" demand for styles. This can be achieved by introducing an additional constant characteristic in the derivation process. It turns out that the average long-run style demand is determined by the proportion of stocks belonging to that specific style. In addition, the style demand also nests industry momentum as a special case where characteristics are replaced with industry indicators.

In this case, assets within the same category (e.g., value or growth) receive identical amounts of capital.

2.3 Demand switching between styles

More generally, the return extrapolation assumption implies that the asset demand is a linear combination of past realized returns of risky assets:

$$L_{i,t}^{X} = \frac{1}{\gamma} \sum_{j=1}^{N} \left[\frac{C_i'(\Theta'\Theta)^{-1}C_j}{\sigma_{j,\varepsilon}^2} \left((1-\theta) \sum_{l=1}^{t-1} \theta^{l-1}(P_{j,t-l} - P_{j,t-l-1}) + \theta^{t-1}X_1 \right) \right]. \tag{9}$$

That is, the dependence of the focal asset's demand on other assets' past returns is determined by the joint distribution of risky assets' characteristics. In particular, we have the following proposition:

Proposition 1. ***Style switching.*** *For any risky asset i, the demand of style extrapolator for asset i decreases (increases) in response to the past returns of dual (twin) style assets.*[12]

This proposition suggests that style extrapolators tend to withdraw capital from the focal asset and shift to dual assets when the dual style appears more attractive. Conversely, they augment investments when the twin style has shown recent strong performance. To the extent that the demand of style extrapolators determines the variation in asset prices, we can have the following corollary:

Corollary 1. ***Asset-level cross-correlations.*** *The returns of risky assets tend to decrease (increase) with respect to the past recent returns of their dual (twin) style assets.*

To establish this corollary, one can expand the portfolio choice model presented in this section by introducing fundamental traders, akin to the approach in Barberis and Shleifer (2003) or Barberis et al. (2018). The fundamental trader is boundedly rational and acts as a short-horizon arbitrageur (Shleifer and Vishny, 1997; Barberis and Shleifer, 2003). Then, the equilibrium price and return dynamics can be derived following a procedure similar to that outlined by Barberis and Shleifer (2003). The subsequent analysis concentrates on the empirical implementation of asset styles and investigates the implied cross-stock return predictability. I also study the trading behavior of various market participants to examine the mechanism highlighted in this section.

[12] Note that $\partial L_{i,t}^{X}/\partial(P_{j,t-l} - P_{j,t-l-1}) = (1-\theta)\theta^{l-1}C_i'(\Theta'\Theta)^{-1}C_j/\gamma\sigma_{j,\varepsilon}^2$. Given that $(1-\theta)\theta^{l-1} > 0$, the proposition follows directly from the definition of dual and twin style assets.

3 Data and variable construction

3.1 Data

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 exclude financial firms and stocks with a share price below $1 at the portfolio formation date. Monthly time series of asset pricing factors are downloaded from Kenneth French's Data Library (Fama and French, 1996, 2015) and the *Global-q* website (Hou et al., 2015, 2021). I also obtain 13F institutional investor holdings data from Thomson Reuters and analyst forecast data from the Institutional Brokers Estimate System (IBES) detail file.

3.2 Constructing dual and twin styles

The initial step in the process of identifying styles is the definition of the characteristic space. I consider five prevailing dimensions, including value, profitability, investment, volatility, and momentum.[13] The construction of characteristics follows the standard procedure of the literature (Fama and French, 1996, 2015; Hou et al., 2020): (1) *Value.* The book-to-market ratio is calculated as the book equity divided by the December market capitalization; (2) *Profitability.* Operating profit is total revenue (Compustat annual item REVT), minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), and minus interest expense (item XINT), scaled by book equity; (3) *Investment.* Asset growth is the percentage change of total assets (item AT); (4) *Volatility.* Return volatility is the standard deviation of monthly stock returns in the past five years, requiring a minimum of 36 available observations; (5) *Momentum.* Momentum is the cumulative stock return in the prior 11 months (skipping the most recent month). Since returns tend to display short-term reversals when the formation period is less than six months, I require a minimum of seven available observations to calculate the momentum variable if there are missing monthly returns. Characteristics are cross-sectionally standardized to have zero mean and unit variance.

I choose these style dimensions for several reasons. First, value, profitability, and

[13] In my main analysis, size (i.e., log of market capitalization) is not included as a style dimension for two primary reasons. First, size is predominantly related to passive investing (e.g., Russell indices or S&P 500 index) and thus less relevant to style switching, which implies highly active investment strategies. Second, the size distribution exhibits extreme skewness, and the computation would be sensitive to the method used to adjust market value. Nevertheless, the pricing effect of dual and twin styles remains valid when size is integrated into the style identification process. In robustness tests, I also show that highly active institutions display the style-switching demand instead of passive ones.

investment factors are prominently featured in prevalent asset pricing models such as Fama and French (2015), showing that factors based on these characteristics explain a substantial portion of anomaly returns. Second, momentum and volatility are also incorporated because of their widespread adoption within the asset management industry for designating trading strategies. Finally, recent research such as Clarke and Linn (2022) suggests that these dimensions are also important in explaining the covariance structure of stock returns. In the robustness section, I shall show that each characteristic contributes to the style pricing effect, and my main result does not solely rely on some specific characteristic combinations.

The second step is to calculate pairwise correlations in characteristics among stocks, which distinguishes between dual and twin styles. In an ideal environment where the model is correctly specified and the observed data sufficiently captures investors' preferences, one can simply separate dual and twin styles based on the sign of these correlations. However, the true asset demand is unobservable, and variables are prone to measurement errors. Therefore, I adopt a conservative approach. Specifically, in each construction, I first calculate the cosine similarities between stocks:

$$COS_{i,j} = \frac{C_i \cdot C_j}{\|C_i\| \|C_j\|}, \tag{10}$$

where C_i and C_j represent the characteristic vectors of firms i and j, respectively. The numerator $C_i \cdot C_j$ is the inner product of the two vectors, and $\| \cdot \|$ denotes the ℓ^2 norm operator (i.e., $\|C_i\| = \sqrt{C_i \cdot C_i}$). Then, for each firm i, the dual and twin styles are defined as follows:

$$Dual\ Style = \{j | j \neq i,\ COS_{i,j} < -\delta\}, \quad Twin\ Style = \{j | j \neq i,\ COS_{i,j} > \delta\}, \tag{11}$$

in which $\delta \in [0, 1)$ governs the precision and inclusiveness of the computation. Figure 1 provides a visual representation of dual and twin styles within a two-dimensional characteristic space. A larger δ yields a stricter definition of dual and twin styles, which, in turn, leads to narrower sets of these styles. Conversely, a smaller δ widens the scope of dual and twin styles but at the expense of precision. In my main analysis, δ is set to 0.25. Nevertheless, in the Appendix, I show that the pricing results are similar for alternative δ choices. In addition, I exclude firm pairs that are in the same four-digit SIC industry to control for the fundamental linkages related to industry labeling. My results are similar when using alternative industry definitions or keeping all firm pairs in the construction process.

Dual and twin styles are formed on an annual basis. At the end of June of each year t, I calculate cosine similarities among stocks based on equation (10). For each stock, the sets of dual and twin styles are determined by equation (11). Starting from July of year t and extending through June of year $t+1$, the stock-specific signal, DUAL (TWIN), is computed as the value-weighted average monthly return of other stocks belonging to the dual (twin) style.[14]

3.3 Summary statistics

Table 1 reports the summary statistics of portfolios sorted by DUAL and TWIN, respectively. I consider a battery of additional firm characteristics in the return predictability test, including the focal stock's monthly return, the idiosyncratic volatility (Ang et al., 2006), firm size, and illiquidity (Amihud, 2002). I also control for the salience theory value (Cosemans and Frehen, 2021) because of its high correlation with monthly stock returns. Regarding style returns, Panel A of Table 1 shows that the focal stock's contemporaneous monthly return is lower when the dual-style return is high. This relationship aligns with the story that style switching affects asset prices, that is, the return comovement between stocks in distinct styles should be smaller than their correlation in cash-flow shocks because of the externalities generated by style-switchers' demand. As dual-style stocks, by construction, generally share opposite directions in fundamentals with the focal stock, it follows that DUAL and the focal stock's contemporaneous return would exhibit a negative comovement.

For extreme quintiles, Table 1 shows that stocks in the top DUAL (TWIN) group display downside (upside) salience, and have lower (higher) long-term returns and book-to-market ratios, than stocks in the bottom group. Stocks in the extreme DUAL or TWIN quintiles have lower asset growth than those in the middle quintile, whereas the operating profits are negative for stocks in the bottom DUAL/TWIN quintile. Nevertheless, firm characteristics are nearly equally distributed across DUAL and TWIN quintiles, and monotonic patterns are absent.

4 Empirical analysis

This section presents empirical evidence on the asset pricing implications of demand switching between styles. I first conduct one-sort portfolios based on dual- and twin-style returns to examine the key theoretical prediction (i.e., the cross-reversals and cross-momentum in stock returns). Then, I perform a series of Fama-MacBeth regressions to control for other potential

[14] To mitigate the concern that, for some firm-month observations, the resulting style signals might be dominated by a few large firms, I winsorize stocks' market capitalization at the 1% and 99% levels cross-sectionally when computing DUAL and TWIN. I also consider alternative weighting schemes in robustness tests. My main findings are insensitive to this specification.

confounding factors. In addition, I also study the role of macroeconomic conditions and the long-horizon returns of style strategies to tease out the potential channels. To further inspect the mechanism underlying the return predictability result, I examine institutional investors' trading on style returns. Last, I complement the evidence on style investing by studying and comparing the trading of short sellers and retail investors.

4.1 Cross-correlations from style switching

This section examines the main prediction regarding cross- and within-style return autocorrelations. Each month, stocks are sorted into quintile portfolios based on DUAL and TWIN, respectively. Portfolios are held for one month and rebalanced each month. Table 2 reports the value-weighted average returns of quintile portfolios and the value-weighted (VW) and equal-weighted (EW) average returns to the strategy that buys stocks in the top quintile and sells stocks in the bottom quintile.

Consistent with my hypothesis, dual styles exhibit cross-stock reversal, whereas twin styles exhibit cross-stock momentum. Specifically, high-DUAL stocks *underperform* low-DUAL stocks by 1.00% per month and are highly significant (t-stat=-4.60). That is, if a stock's dual-style peers have performed relatively well in the recent past, the focal stock tends to yield lower returns because of the shifting in demand. The return of the dual-style strategy is also robust to the adjustment of prevailing asset pricing factors. For instance, the hedge portfolio based on DUAL generates a five-factor (Fama and French, 2015) alpha of -1.02% per month and a q-factor (Hou et al., 2015) alpha of -1.08% per month. This cross-reversal effect becomes even stronger when accounting for the short-term autocorrelation of the focal stock itself. In particular, the seven-factor alpha (FF6+Rev) of the DUAL strategy, which adjusts for the Fama and French (2015) factors, momentum, and the short-term reversal factor, stands at -151 bps (t-stat=-7.72) for value-weighted portfolios and -160 bps (t-stat=-8.77) for equal-weighted portfolios. This finding probably arises because of the negative comovement between DUAL and the focal stock's contemporaneous return. The performance of the dual-style strategy is enhanced by controlling for the short-term reversal effect, which is mainly driven by factors other than style investing, such as illiquidity (Avramov et al., 2006; Nagel, 2012; Dai et al., 2023).

Conversely, high-TWIN stocks *outperform* low-TWIN stocks with a monthly spread of 1.02% (t-stat=4.92). This performance holds robustly across various factor models, with a monthly alpha ranging from 0.98% to 1.57%. Similar to DUAL, the predictive ability of TWIN becomes more pronounced after controlling for the focal firm's short-term reversal effect. This is evident in the average seven-factor alpha (FF6+Rev) of over 1.50%. The existence of cross-momentum in twin styles is not unique to this paper, as previous studies such as Lewellen (2002), Chen (2003), Wahal and Yavuz (2013), Chou et al. (2019), and He et al. (2023) have also shown that past returns of firms with similar characteristics positively predict cross-sectional expected returns. Hence, the predictive ability of TWIN alone does not adequately substantiate the price impact of style switching. The novel finding of this paper, however, is the negative lead-lag returns relation among stocks classified as dual styles. While the mechanism underlying the momentum spillover effect of twin-style stocks might be mixed, the cross-reversals among dual-style stocks pertain more closely to the style investing channel in affecting asset prices.

An additional property regarding the style pricing effect is that the magnitude of reversals and momentum should be similar. This is because, in a frictionless market, capital flows switch perfectly between dual and twin stocks, leading to price fluctuations that closely resemble each other. Panel C of Table 2 tests this corollary formally. It reports the average return of the sum of the two style strategies. For most specifications, I find that the difference in return magnitudes between DUAL and TWIN strategies is not distinguishable from zero. This "symmetric" result also highlights a potential virtue of my empirical design on dual and twin styles. Traditional constructions, such as sorted portfolios or industry classifications, inherently impose an asymmetric structure and are less aligned with the style-switching story.

One concern regarding the return predictability result, however, is that DUAL and TWIN are potentially correlated. Since by construction, dual- and twin-style stocks exhibit opposite directions in their underlying fundamentals, DUAL would negatively correlate with TWIN to the extent that stock returns reflect the movement of fundamentals. In addition, the predictive ability of TWIN is less surprising because of other confounding effects such as the traditional positive feedback trading channel (De Long et al., 1990) or the initial underreaction to fundamental news (Cohen and Frazzini, 2008). Therefore, the result associated with DUAL might also be anticipated ex ante because of its correlation with TWIN. To address this concern, I conduct monthly cross-sectional regressions of DUAL against TWIN and take the residuals. If the cross-stock reversal stems from a pure statistical correlation with TWIN, then the residual DUAL should not exhibit any predictive ability for future returns. The result is reported in Table 3. Panel A shows that the residual DUAL still displays significant predictive power for the focal stock's return even after purging out its correlation with TWIN. On the contrary, the pricing effect of TWIN is dominated by DUAL. Panel B shows that the residual TWIN, which eliminates the correlation with DUAL, loses most predictive ability. This result suggests that the cross-stock reversal of dual styles is primarily driven by the switching of demand rather than the mechanical relationship between the two proposed style returns. It also implies that style switching is responsible for the predictive power of TWIN, which should not be solely attributed to other channels. In later analysis, I perform a battery of additional tests to further distinguish between style switching and alternative explanations.

4.2 Fama-MacBeth regressions

Although the above portfolio approach is simple and intuitive, it cannot explicitly control for other characteristics that might predict returns, especially other lead-lag effects with mechanical ties to style returns. In particular, as implied by theory and reported in Section 3.3, DUAL and TWIN are negatively correlated. By construction, TWIN tends to positively correlate with other variables such as industry returns since industry peers share similar fundamentals. As a result, one might worry that the predictive ability of dual- and twin-style returns is a direct consequence of such statistical correlations. Therefore, I examine the cross-correlations from style switching using Fama-MacBeth regressions. I control for various alternative cross-firm return predictors, such as the industry return (Moskowitz and Grinblatt, 1999; Hou, 2007), the value-size style return (Lewellen, 2002; Wahal and Yavuz, 2013), and the shared analyst coverage return (Ali and Hirshleifer, 2020).[15] Table 4 presents the regression results. Columns (1) and (6) present the coefficients of DUAL and TWIN, respectively, while controlling for the focal firm's own characteristics. Consistent with the portfolio results, I find that DUAL and TWIN exhibit significant predictive ability. A one-standard-deviation increase in DUAL implies a 0.244% decrease in future stock returns, whereas the same change in TWIN corresponds to a 0.191% increase in future returns.

The coefficients show minor changes when controlling for the industry return or the value-size style return. This is expected as dual and twin styles are constructed independently from industry links and rely on composite characteristics. Furthermore, consistent with Ali and Hirshleifer (2020), the shared analyst coverage return (CFRET) demonstrates a superior predictive ability for focal stocks' returns. Columns (4) and (9) suggest that the coefficients for DUAL and TWIN decrease by 39% and 29%, respectively, after controlling for CFRET. Nevertheless, the cross-correlations stemming from dual and twin styles remain significant

[15]Specifically, industry return is the value-weighted average monthly return of stocks within the same two-digit SIC code industry. Following Wahal and Yavuz (2013), I categorize stocks into 5×5 portfolios based on market capitalization and the book-to-market ratio. The value-size style return is calculated as the value-weighted average monthly return of other stocks within the same portfolio. Different from Lewellen (2002) and Wahal and Yavuz (2013), I exclude the focal stock and use one-month returns when computing the style return. This modification is taken to mitigate the short-term reversal effect and ensure consistency with the construction of other variables. Following Ali and Hirshleifer (2020), each month, I identify connected firms by joint analyst coverage in the past year. The shared analyst coverage return is the weighted average monthly return of a stock's connected peers. The weight is determined by the number of analysts covering both firms.

at the 1% level. After accounting for the effects of all predictors, the coefficient on DUAL (TWIN) stays at -0.144 (0.139) with a t-statistic of -2.78 (2.77). Overall, the style pricing effect is unlikely to be solely ascribed to correlations with existing lead-lag returns relations. I further verify the validity of my findings by incorporating more inter-firm linkages and conducting spanning regressions in the robustness section.

4.3 Macroeconomic conditions and long-horizon pricing effects

Two alternative explanations are also potentially responsible for the abnormal returns associated with DUAL and TWIN. The first one is that the average twin-style and dual-style stock returns are proxies for *time-varying risk premia*. A large literature models the conditional expected return with firm characteristics being factor (risk) exposures (Daniel and Titman, 1997; Brennan et al., 1998; Daniel et al., 1998, 2020). If the past returns of twin and dual styles represent plausible estimates of the conditional risk premia, then it is possible that stocks with positively (negatively) correlated characteristics display cross-momentum (reversal). The other explanation is the *sluggish diffusion of information*. When investors underreact to fundamental news contained in other stocks' prices, the focal stock's price delays in reflecting value-relevant information, thus generating cross-stock return predictability (e.g., Cohen and Frazzini (2008) and Ali and Hirshleifer (2020)). While twin-style firms indeed share connected fundamentals and potentially correlated cash-flow shocks, it is unclear why underreaction would lead to reversals for dual-style firms. For instance, favorable fundamental shocks for value stocks do not necessarily imply bad news for growth stocks.

Although it is challenging to completely rule out these explanations, examining time variations and long-term returns of style strategies would shed light on the relative importance of style investing. First, if my result is driven by systematic risk, then macro-related variables that have been shown to predict market risk premium should also have predictive power for style effects. Second, the identification of styles is based on statistical metrics rather than real economic connections. Therefore, the autocorrelation in stock returns should reflect lead-lag reactions to common macro shocks if the underreaction hypothesis is responsible for my findings. This again suggests that variations in style effects over time should be predictable by macroeconomic conditions. Finally, if the pricing result of styles is driven by underreaction or time-varying risk premia, then the associated abnormal returns should be persistent. Instead, if the style-switching demand leads to prices deviating from fundamentals, then the strategy returns should reverse eventually.

To examine the role of macroeconomic conditions, I conduct time-series regressions of style strategy returns on lagged macro-related variables.[16] Table 5 shows that variables related to macroeconomic conditions lack predictive ability for style effects. For the dual style, macro-related variables do not predict strategy returns significantly and 7 out of 10 estimated coefficients have a t-statistic with an absolute value smaller than 1. The performance of the dual style strategy also does not heavily rely on market conditions, as the loading on the contemporaneous market premium is insignificant. I find similar results for the twin style, except that the coefficient on lagged cross-sectional premium (CSP) is significant (t-stat=2.12). This difference, in turn, suggests that the dual style provides a clearer representation of style switching. The twin style, by construction, might contain other confounding mechanisms as mentioned in the introduction of the paper. Nonetheless, macroeconomic conditions are not likely to be the main force behind style effects.

Figure 2 shows the long-term performance of the DUAL and TWIN strategies. I follow the methodology of Jegadeesh and Titman (1993) in calculating portfolio returns with a holding period exceeding one month, and I report returns adjusted for market performance.[17] The magnitude of strategy profits tends to grow over the initial one-year horizon for both DUAL and TWIN. However, beyond this point, returns commence a gradual decline over the ensuing 18 months, eventually converging to zero. For horizons extending beyond 30 months post-portfolio formation, the strategy returns even exhibit a slight reversal in sign. Overall, the long-term performance of DUAL and TWIN strategies is more consistent with the style investing story, whereas neglecting fundamental news or the risk-based explanation is less important in driving the result.

4.4 Institutional trading on style returns

The primary mechanism underlying the pricing effects of dual and twin styles, as illustrated in Proposition 1 in Section 2, is the shift in investor demand between these two competing styles. In particular, when past twin-style returns are high, investors lean toward buying the focal stock. Conversely, they tend to divest from the focal stock to fund investments in dual-style assets when dual-style returns are more attractive.

[16] I obtain data on 9 macroeconomic variables from Amit Goyal's website (`https://sites.google.com/view/agoyal145`), including the book-to-market ratio (BM), dividend-price ratio (DP), earnings-price ratio (EP), default yield spread (DFY), term spread (TMS), stock variance (SVAR), inflation (INFL), net equity expansion (NTIS), and cross-sectional premium (CSP). I also obtain data on the trend deviation of consumption to asset wealth and labor income (CAY) from Sydney Ludvigson's website (`https://www.sydneyludvigson.com/`). I thank Amit Goyal and Sydney Ludvigson for making these data available.

[17] The conclusion remains unchanged when using raw excess returns or when controlling for additional asset pricing factors.

To test this mechanism, I investigate institutional investors' trading behavior in response to dual- and twin-style returns with the following regression:

$$\Delta Inst_{i,t+1} = a + b_{style} Style_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}, \tag{12}$$

in which $\Delta Inst_{i,t+1}$ is the quarterly change in institutional ownership, computed as the number of shares held by institutional investors (13F) divided by the total shares outstanding. The main independent variable of interest is the lagged style return ($Style_{i,t}$). If investors indeed switch between dual and twin styles, we would observe institutions trading these style returns in opposite directions, that is, $\hat{b}_{\text{DUAL}} < 0$ and $\hat{b}_{\text{TWIN}} > 0$.

Table 6 reports the results from panel regressions. Columns (1) and (2) of Panel A examine the response of institutional demand to dual styles. It shows that a one-standard-deviation increase in lagged DUAL corresponds to a decrease in $\Delta Inst$ of around 0.072%. On the other hand, columns (3) and (4) show that lagged TWIN exhibits a positive association with $\Delta Inst$, with an estimated coefficient of 0.070. When both variables are included in the regression (columns 5 and 6), the slopes slightly diminish but remain significant at the 5% level. In Panel B, I examine an alternative proxy for variations in investor demand using the percentage change in the number of institutional investors holding the stock (Edelen et al., 2016). Consistently, I find that lagged DUAL is negatively associated with investor demand, whereas TWIN positively predicts the growth in the number of institutional holders.

While institutional investors on average exhibit style investing, the degree of demand switching would be more pronounced for active institutions. For example, while exchange-traded funds (ETFs) and market index funds also employ categorical investment to some extent, the variation in the passive ownership should be less responsible for the style-induced pricing effect. If anything, the potential positive feedback trading from these institutions should contribute to the within-style momentum rather than cross-style reversals. Therefore, I further partition institutions into different types based on the *Institutional Investor Classification* from Brian Bushee's website (Bushee, 2001; Bushee and Noe, 2000).[18] Specifically, institutional investors are classified into six categories: (1) bank trust (BNK); (2) insurance company (INS); (3) investment company (INV); (4) independent investment advisor (IIA); (5) pension fund (PSF); and (6) other institutions (OTHER).[19] For each type of institutional investor, I calculate changes in ownership and perform analogous regressions

[18] Brian Bushee, "Institutional Investor Classification Data (1981-2021)," `https://accounting-faculty.wharton.upenn.edu/bushee/`

[19] The pension fund ownership is the sum of ownership of corporate (private) pension funds and public pension funds. Institutions classified as university and foundation endowments, miscellaneous, or having missing labels are defined as others.

as in equation (12) to investigate the propensity of style investing.

Table 7 presents the results. It shows that independent investment advisors alone dominate the overall effects depicted in Table 6. A one-standard-deviation increase in lagged dual-style returns is associated with a decrease in focal stocks' IIA ownership of around 0.053%, whereas an increase in twin-style returns implies IIA purchasing focal stocks (with an estimated coefficient of 0.057). Both effects are highly significant. In general, IIA consists of wealth management companies, hedge funds, private equities, and other firms with professional and specialized investment strategies. This result aligns with the hypothesis that active institutions engaging in style investing act as marginal investors that affect prices. Previous studies also demonstrate that most hedge funds employ highly dynamic strategies and change investment styles frequently (Fung and Hsieh, 1997; Bollen and Whaley, 2009; Jiang et al., 2022). In the context of style investing, Wermers (2012) and Frijns et al. (2016) find that active mutual fund managers engage in style-level feedback trading and switch between styles; Schauten et al. (2015) further show that hedge funds exhibit a greater tendency to manage portfolios at the style level. This evidence lends support to my findings.

Investment companies also trade style returns in the same direction as IIA, although the magnitude of trading propensities is much smaller and marginally significant. For example, the estimated coefficient on the dual-style return is -0.009 with a t-statistic of -1.52. The primary reason is that many investment companies (e.g., mutual funds) adopt passive investment strategies. As mentioned earlier, while the demand from institutions such as index funds and ETFs indeed causes them to specialize their investment to a market-wide sense, the incentive to switch is less pronounced compared with highly active institutions.[20] For other institutional investors, Table 7 shows that banks and pension funds do not trade on style performance. Insurance companies and other institutions exhibit a weak tendency toward style switching but the estimated coefficients are not distinguishable from zero.[21] Notably, these results also accord with Koijen et al. (2023) that hedge funds and small-active investment advisors are more influential for equity pricing, whereas long-term investors such as pension funds and

[20]Another possible explanation is that individuals are the dominant and ultimate investors of mutual funds. As a result, the investment decisions of mutual fund managers are largely affected by fund flows. While individual investors are also prone to employ categorical thinking because of limited attention (Peng and Xiong, 2006) and hence adopt a style-based strategy, the potential discrepancy in preference between fund managers and individual investors could diminish the demand-switching effect.

[21]As a robustness test, I also examine the trading of institutional investors based on their activeness. Bushee (2001) and Bushee and Noe (2000) classify institutional investors into three categories: (1) *dedicated*: institutions with low turnover; (2) *transient*: institutions with high turnover; and (3) *quasi-indexer*: institutions tracking indices. Following Chen et al. (2022), I regard transient institutions as being highly active investors. Consistent with the result in this section, Appendix Table A1 shows that transient institutional investors exhibit a strong tendency to switch styles, whereas institutions classified as dedicated or quasi-indexer do not actively engage in style switching.

insurance companies have relatively small impacts.

4.5 Trading of short sellers and retail investors

The result in the previous section suggests that institutional investors indeed switch their funds between dual and twin styles. However, less is known about whether professional traders engage in style investing by short selling, as the Thomson-Reuters 13F database only tracks long positions. Short sellers are widely believed to be highly professional and well-informed investors. Prior studies such as Drake et al. (2011) and McLean et al. (2020) indeed find that short sellers trade on the profitable side of anomalies. Boehmer et al. (2008) show that institutions, especially hedge funds, account for most short sales. In this section, therefore, I investigate whether the trading behavior of short sellers aligns with style investing. Another important group of market participants is retail investors. It is worth noting that the framework presented in Section 2 does not involve assumptions about investor sophistication. The style-switching behavior also applies to retail investors as they are prone to employ categorical thinking (Peng and Xiong, 2006; Huang, 2019) and exhibit return extrapolation (Greenwood and Shleifer, 2014; Da et al., 2021). Thus, I also study the response of retail investors' demand to style returns.

I follow the methodology of McLean et al. (2020) to measure the trading of short sellers and retail investors. Specifically, I retrieve the monthly short interest data from the Compustat - Supplemental Short Interest File. The monthly short interest ratio (SI) is calculated as short interest scaled by shares outstanding. Changes in SI reflect the trades of short sellers. For the retail investor data, I retrieve daily retail trading volume from the WRDS - TAQ Millisecond Tools, which identifies retail trades using the algorithm of Boehmer et al. (2021).[22] As in McLean et al. (2020), daily retail trading is calculated as retail buys volume minus retail sells volume, scaled by shares outstanding. This construction allows for direct comparisons with trading metrics related to short sellers and institutional investors. The monthly retail trading variable is computed by aggregating retail investors' daily percentage of net purchases.

Table 8 reports the trading of short sellers and retail investors over different horizons. Each month, I form sorted portfolios based on DUAL and TWIN, respectively. For each portfolio, I calculate the value-weighted average of subsequent trading measures over different holding periods. This computation is analogous to the method employed in Section 4.3. Panel A shows that short sellers tend to increase (decrease) the short interest of focal stocks when the dual style return is high (low). Over the 1-month to 3-month periods, the variation in

[22] For more details on the retail trading data, please refer to Wharton Research Data Services, `https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-intraday-indicators/`

changes in short interest between high- and low-DUAL stocks primarily arises from the short (or low-DUAL) side. Short sellers gradually establish selling positions in high-DUAL stocks over a 6-month to 12-month period, followed by a slow down of trading. This pattern is consistent with the long-term pricing result depicted in Figure 2, which shows that the return magnitude of the DUAL strategy tends to increase within a 1-year horizon and then decrease for longer horizons. For the twin style, Panel B suggests that short sellers decrease short interest for high-TWIN stocks. The difference in changes in SI between high- and low-TWIN stocks is significant for periods up to 12 months, and the spread is insignificant for longer horizons. In addition, short sellers do not exhibit a strong tendency to sell low-TWIN stocks. Overall, the trading behavior of short sellers aligns with the prediction of style switching.

Panels C and D of Table 8 present the results of retail trading. I find that retail investors purchase focal stocks more when the twin-style return is high or when the dual style performs poorly. On average, attractive dual-style returns or disappointing twin-style returns are not associated with net retail selling. Distinct from the trading of short sellers, the difference in retail trading between high- and low-style return portfolios is significant only over the long horizon. While this result supports the notion of style switching, the trading trend across style portfolios appears less consistent compared to that observed among short sellers. In addition, retail trading is more persistent than short sellers' trades. For example, retail investors purchase low-DUAL stocks aggressively even 30 months after portfolio formation, at which point the DUAL strategy does not earn profits, as illustrated by Figure 2. This pattern is consistent with the finding of McLean et al. (2020) that retail investors continue their trading tendency for a long period after the time of anomaly portfolio formation.

In sum, I find supportive evidence on style switching among both short sellers and retail investors, with the evidence being more pronounced for the former group. Notably, the result suggests that professional investors appear to be more responsible for style-induced pricing effects, whereas retail investors act as trend followers.

5 Additional tests

This section provides several robustness tests. I first study the role of institutional investor attention by exploring the time variation in style effects. Then, I conduct a series of spanning tests using a battery of prevailing lead-lag effects. Last, I assess the robustness of the return predictability result by examining alternative specifications of the style variables.

5.1 Time variation in institutional attention and style effects

Institutional investors play a dominant role in style investing. As shown in Section 4.4, highly active institutions exhibit a stronger tendency to switch styles. Section 4.5 also implies that professional investors, as opposed to retail investors, account more for style pricing. These findings indicate that the cross-firm reversals and momentum would be stronger following periods when institutional investors pay more attention. To test this prediction, I use Bloomberg's daily maximum readership (DMR) as a measure of institutional investor attention, as in Ben-Rephael et al. (2017). DMR is a daily-level score assigned to each stock and represents Bloomberg users' searches and readership for a given stock relative to its distribution during the past 30 days.[23] Following Ben-Rephael et al. (2017) and Da et al. (2023), abnormal institutional attention is defined as a dummy variable that takes a value of one if DMR is 3 or 4, and zero otherwise. Then, the aggregate institutional investor attention (AIA) is calculated as the value-weighted average of individual stocks' abnormal institutional attention indicators.

In Panel A of Table 9, I follow the methodology of Stambaugh et al. (2012) to separate the sample into high- and low-AIA periods. I first extract monthly AIA by taking month-end AIA values. Then, a high-AIA month is designated when the month-end AIA surpasses the median value for the sample period, while low-AIA months are identified by values falling below the median. I find that the abnormal returns of the DUAL and TWIN strategies are earned *entirely* following months with high levels of institutional attention. For example, the magnitude of the factor-adjusted return of the DUAL strategy exceeds 1.1% following high-AIA months, whereas the return spread is around zero otherwise. Importantly, the difference in returns between high- and low-AIA periods is significant at the 5% level. For the TWIN strategy, the long-short portfolio earns a positive return following high-AIA months; in sharp contrast, the return spread of TWIN portfolios is negative following low-AIA months. The difference in the TWIN strategy returns between high- and low-AIA periods is economically large, albeit only marginally significant. This evidence supports the hypothesis that institutional investors' style-switching demand is responsible for the documented cross-stock autocorrelations.

An important feature of AIA is that it tends to be positively correlated with *retail* attention (Ben-Rephael et al., 2017; Da et al., 2023). Therefore, the previous result might potentially be driven by the excess demand of retail investors, as in He et al. (2023), instead of institutional investors' switching demand. To address this concern, I conduct predictive regressions using AIA and control for the effect of retail attention. Specifically, retail investor

[23] See Ben-Rephael et al. (2017) for more details on DMR.

attention is measured by abnormal Google search volume, as in Da et al. (2011). Then, the aggregate retail attention (ARA) is computed as the value-weighted average of individual stocks' abnormal Google search volume (Da et al., 2023). I also control for the investor sentiment index of Baker and Wurgler (2006) since Stambaugh et al. (2012) demonstrate that many asset pricing anomalies become more pronounced following high sentiment periods.

Panel B of Table 9 reports the regression results. Consistent with the findings in Panel A, I find that AIA negatively predicts subsequent DUAL strategy returns while positively predicting TWIN strategy returns. As a comparison, ARA does not exhibit any predictive ability for style effects. When incorporating all predictors, in Panel B, columns (3) and (6) show that a one-standard-deviation increase in AIA implies enhanced cross-reversal by 0.77% (t-stat=-2.53) and cross-momentum by 0.64% (t-stat=2.10), yet ARA is positively (negatively) correlated with future DUAL (TWIN) returns. This result contradicts the conjecture that retail investors' demand drives the cross-predictability of dual and twin styles. Crucially, He et al. (2023) find that ARA is a strong predictor for their similarity effect. In sharp contrast, Table 9 suggests that retail investor attention is less important in the style pricing effect. Overall, while the construction of styles in this paper shares some commonalities with He et al. (2023), the mechanism underlying the documented predictability appears to be distinct.

5.2 Spanning tests

A fast-growing literature documents a prevailing cross-firm return predictability from economic linkages. Beyond the traditional industry momentum (Moskowitz and Grinblatt, 1999; Hou, 2007), several representative examples include customer-supplier relationships (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), conglomerate firms (Cohen and Lou, 2012), text-based industry momentum (Hoberg and Phillips, 2018), technological links (Lee et al., 2019), geographic momentum (Parsons et al., 2020), and shared analyst coverage (Ali and Hirshleifer, 2020).[24] While these lead-lag effects are primarily driven by investor underreaction, the returns of style strategies are more consistent with a continued overreaction story. However, there could be mechanical connections between economic linkages and style investing that also contribute to the predictive ability of style returns. For instance, firms with common analyst coverage tend to exhibit positively correlated fundamentals (Ali and Hirshleifer, 2020), thus overlapping the empirical construction of twin styles. While it remains unclear whether the definition of dual styles can be explicitly linked to economic connections, statistical

[24] I obtain 10-K text-based similarity data from the Hoberg-Phillips Data Library, and the patent data are provided by Kogan et al. (2017). For brevity, the construction details of these linkage variables are presented in the Appendix.

correlations between style returns and economic links might also drive both cross- and within-style predictability in this paper.

To address this concern, I conduct additional spanning tests to assess the robustness of my results. In a recent study, He et al. (2023) use the Euclidean distance between stocks' characteristics and find that the thus-defined "similar stocks" (SIM) also exhibit strong cross-firm momentum. While the mechanism underlying similar stocks is the excess demand of retail investors, the style pricing effect, as shown in the previous section, highlights the role of institutional investors. Nevertheless, I also incorporate the SIM strategy in my tests. Table 10 reports the results from time-series spanning regressions. It shows that, even after controlling for several prevailing lead-lag effects simultaneously, the returns associated with dual and twin styles remain significant. This result suggests that style investing provides incremental information about return autocorrelations beyond conventional inter-firm linkages.

5.3 Alternative specifications of dual and twin styles

5.3.1 Style returns orthogonal to the short-term reversal effect

It is well-documented that stock returns tend to exhibit reversals at short horizons.[25] Although style investing gives rise to a rich set of predictions regarding cross-correlations, it is almost silent on explaining short-term own-autocorrelations. In fact, the short-term reversal effect is predominantly interpreted as compensation for illiquidity (e.g., Avramov et al. (2006); Nagel (2012); and Dai et al. (2023)). As shown in Section 3.3, DUAL (TWIN) is negatively (positively) correlated with the focal stock's contemporaneous monthly return. Therefore, the pricing result of dual and twin styles might be contaminated by such correlations, and the predictive ability of DUAL and TWIN would be stronger after purging out the short-term reversal effect. I orthogonalize the dual- and twin-style returns against the focal stock's own month return and report the strategy returns in Appendix Table A2. It shows that the equal-weighted return of the DUAL strategy is -1.509%, suggesting a 26% increase relative to the benchmark result (-1.202%), as reported in Table 2. The improvement is more pronounced in terms of Sharpe ratios when examining value-weighted portfolios. This is evident in the small increase in return magnitudes but the decrease in strategy volatilities (i.e., increase in the magnitude of t-statistics).

[25] See, for example, Jegadeesh (1990); Lehmann (1990); Kaul and Nimalendran (1990); Lo and MacKinlay (1990); and Campbell et al. (1993).

5.3.2 Parameter choice and weighting scheme

The empirical implementation of dual and twin styles relies on calculating cosine similarities between firms. As discussed in Section 3.2, the parameter δ determines the precision and inclusiveness of the construction. While I have used $\delta = 0.25$ for my main analysis, I examine alternative δ values in this section for robustness checks. The results are reported in Appendix Table A2, and δ is chosen from $\{0.15, 0.20, 0.30\}$. I find that the resulting DUAL and TWIN still display strong predictive ability for future returns, and the directions are consistent with theoretical predictions. In addition, I also explore alternative weighting schemes for style returns. Instead of using value-weighted returns of dual/twin stocks, I examine (1) equally weighted returns and (2) absolute cosine similarity-weighted returns. These results are also reported in Appendix Table A2. Consistent with my main findings, it is shown that dual-style returns significantly and negatively predict focal stocks' subsequent returns, whereas twin-style returns exhibit strong and positive predictive power.

5.3.3 Alternative combinations of characteristics

I have thus far focused on five prevailing characteristics relevant to style investing and tested return predictability using composite styles. To address the concern that my findings are dominated by a few characteristics, I examine styles from subsets of these characteristics. In Appendix Table A3, I use two (Panel A), three (Panel B), or four (Panel C) of the five characteristics to construct dual and twin styles. I find that the constructed DUAL (TWIN) negatively (positively) predicts returns in most specifications. Since I only use subsets of the baseline characteristics, the strategy performance is indeed weaker on average. Nevertheless, most resulting styles continue to deliver robust cross-firm return predictability, and there is little redundancy among the characteristics.

5.3.4 A placebo test using return correlation-based styles

The definition of the two competing styles (i.e., dual and twin) relies on the correlation between assets *in terms of characteristics*. A counterpart construction is to define dual and twin styles using *return* correlations. For example, the style-level capital allocation suggests that style-connected stocks should exhibit excessive comovement. As a result, one might worry that simply using correlations in stock returns is also sufficient to identify dual and twin styles. However, relying solely on correlations in stock returns lacks clear theoretical justification, despite its empirical feasibility. Furthermore, although style investing implies excess comovement, the reverse is not necessarily true when finding styles.

As a placebo test, I construct pseudo dual- and twin-styles based on the return correlations among stocks. Specifically, for each stock pair (i, j), I first compute their correlation $(\rho_{i,j})$ using daily stock returns within a month. Then, for any given stock i, the set of pseudo-dual (twin) style stocks, $\{j\}$, consists of stocks with $\rho_{i,j} < -0.25$ $(\rho_{i,j} > 0.25)$. The pseudo-style returns are then computed as the value-weighted average monthly return within each style. Appendix Table A4 reports the strategy returns by sorting stocks based on pseudo-style returns. It shows that styles constructed from return correlations fail to generate significant style-switching effects. I further control for the influence of short-term reversal by using residuals from cross-sectional regressions of pseudo-style returns on the focal stock's monthly return as predictors. Across different specifications, pseudo-style returns do not display any predictive ability for focal stocks' future returns.

6 Extension to factor momentum and reversals

As a supplement to the main result, this section extends the analysis of asset-level cross-autocorrelations to factor-level return predictability. I first introduce factor returns and factor demand within the framework in Section 2. Then, a simple characterization of factor-level demand switching is presented. Last, I provide empirical evidence on the predictable reversal and momentum effects in factor returns based on an extensive cross section of characteristics (factors) data.

6.1 From style investing to factor switching

Consider the economy described in Section 2. A factor k, or a trading strategy based on characteristic k, is represented by $S_k'\mathbf{R}_t$, where $\mathbf{R}_t$ is the vector of asset returns (i.e., $\mathbf{P}_t - \mathbf{P}_{t-1}$) and S_k is an $N \times 1$ vector of characteristic values. For example, let k be the earnings-to-price ratio (EP). Intuitively, $S_k'\mathbf{R}_t$ is the return to a trading strategy (factor) that buys high-EP stocks and sells low-EP stocks, where we think of the normalized EP signal as the portfolio holding.[26]

The *factor demand* of k, denoted as $S_k'\mathbf{L}_t^X$, is the inner product of the characteristic vector and the individual asset demand. In essence, $S_k'\mathbf{L}_t^X$ measures the degree to which the demand from the style investor corresponds to this specific factor. Our focus lies in understanding the response of factor demand to past factor returns. Specifically, we have the following proposition:

[26]This representation is widely used in related literature. See, for example, Kozak et al. (2020) and Kelly et al. (2023).

Proposition 2. ***Factor demand switching.*** *For a factor p and another factor q, the demand for p decreases (increases) in response to the past returns of q if the characteristics S_p and S_q are negatively (positively) correlated, i.e., $S_p' \left[\Theta(\Theta'\Theta)^{-1}\Theta'\mathbf{\Gamma}^{-1}\right] S_q > (<) 0$.*[27]

This relation holds even if the style extrapolator does not directly trade factors p and q. That is, the factors of interest, S_p and S_q, are not necessarily columns of Θ. The reason is that style switching implies that the demand for any risky asset is a linear combination of all assets' past returns, style extrapolators decide their trades based on transient fluctuations in recent prices, regardless of the underlying profitability of factors. Therefore, the marginal demand for any characteristic-based linear strategy (e.g., a factor) would be influenced implicitly by the past performance of another one.

Similar to Section 2, for any factor p, we can define the *dual* factors and *twin* factors based on their correlations within the asset universe. Specifically, the set of dual (twin) factors consists of linear strategies sharing negative (positive) correlations with the focal factor in their underlying characteristics. Then, we have the following corollary:

Corollary 2. ***Factor-level autocorrelations.*** *The returns of factors tend to decrease (increase) with respect to the past returns of their dual (twin) factors.*

In particular, when $p = q$, the above corollary implies the own-factor momentum as studied in Gupta and Kelly (2019), Ehsani and Linnainmaa (2022), and Arnott et al. (2023).

6.2 Empirical evidence on factor return predictability

To examine the cross-factor and own-factor return predictability, I obtain a large set of firm-level characteristics from the *Open Source Asset Pricing* database (Chen and Zimmermann, 2021).[28] I start with 204 firm-level return predictors and keep continuous variables. I further require at least 50 available stocks each month and exclude characteristics with less than 10 years of available data.[29] This process leaves me with 171 firm characteristics in total. Each month, for each characteristic, I form value-weighted portfolios by sorting stocks into quintiles based on their characteristics. Then, the factor returns are calculated as the difference between the top and bottom quintile portfolios.

[27] Note that $\partial S_p'\mathbf{L}_t^X/\partial S_q'\mathbf{R}_{t-1} = S_p'(\partial\mathbf{L}_t^X/\partial\mathbf{R}_{t-1})S_q = \frac{1}{\gamma}S_p'\Theta(\Theta'\Theta)^{-1}\Theta'\mathbf{\Gamma}^{-1}\left[\partial\mathbb{E}_t^X[\mathbf{P}_{t+1}-\mathbf{P}_t]/\partial\mathbf{R}_{t-1}\right]S_q$. The return extrapolation assumption implies that $\partial\mathbb{E}_t^X[\mathbf{P}_{t+1}-\mathbf{P}_t]/\partial\mathbf{R}_{t-1} = diag(1-\theta,...,1-\theta)$, where $\theta \in (0,1)$ and hence $1-\theta > 0$. It follows that $\partial S_p'\mathbf{L}_t^X/\partial S_q'\mathbf{R}_{t-1} > (<)0$ if $S_p'\left[\Theta(\Theta'\Theta)^{-1}\Theta'\mathbf{\Gamma}^{-1}\right]S_q > (<)0$.

[28] For more details on the dataset, please refer to Open Source Asset Pricing, `https://www.openassetpricing.com/`. The empirical analysis in this section utilizes the March 2022 release. I am grateful to Andrew Chen and Tom Zimmermann for making the data available.

[29] Only one characteristic fails to meet this requirement: the institutional ownership among high short interest (Asquith et al., 2005), denoted by "IO_ShortInterest" in the database.

At the end of each June, I calculate pairwise correlations between (standardized) characteristics. Each computation is conducted cross-sectionally, equivalent to calculating inner products between characteristics within the asset space. For each of the 171 factors, the set of dual (twin) factors is defined as factors sharing negative (positive) correlations in their underlying characteristics. For example, suppose that in June 2000, there were 70 characteristics negatively correlated with the book-to-market ratio (BM), while the remaining 100 displayed positive correlations with BM. Then, the BM-specific dual (twin) factors are defined as long-short strategies derived from the corresponding 70 (100) characteristics. This classification remains fixed throughout the following 12 months until the next June, at which point dual and twin factors will be reassigned. Then, for each individual factor (i.e., a long-short trading strategy) from July of year t to June of year $t+1$, the dual-factor return and twin-factor return are calculated as the weighted average monthly return of its dual factors and twin factors, respectively. I use the absolute value of correlations between the underlying characteristics as the weights.

Table 11 reports the average monthly returns and alphas for factor-trading strategies. To be specific, I respectively sort focal factors into quintiles each month based on dual-factor returns, twin-factor returns, and their own returns, in the last month. Then, the factor-trading strategy longs factors within the top quintile and shorts those within the bottom quintile. Panel A and Panel B report the results of cross-factor predictability. Consistent with the factor-switching hypothesis, dual factors exhibit cross-factor *reversals*, whereas twin factors display cross-factor *momentum*. In terms of economic magnitude, the dual-factor strategy generates a monthly return of -0.982% (t-stat=-6.15) and a six-factor alpha (Fama and French, 2015) of -0.877% (t-stat=-4.57) per month. In sharp contrast, the twin-factor strategy earns positive profits, with a monthly return of 1.01% (t-stat=6.08) and a six-factor alpha of 0.948% (t-stat=4.67). Panel C shows the strategy performance based on factors' own lagged returns. Consistent with prior studies on factor momentum, this strategy also generates significant and positive returns across various model specifications.

Overall, the result presented in this section complements the findings on stock-level return predictability. It suggests that style investing might exert a broader and deeper impact on asset prices. Recent studies such as Green et al. (2013), Chen and Zimmermann (2021), and Chen and McCoy (2022) document that the correlation between characteristics is minor and generally clusters around zero. The cross-factor predictability suggests that strong intertemporal dependence in factor returns still exists despite the low-correlation structure of characteristics and contemporaneous factor returns. It also provides a potential explanation for the finding of Kozak et al. (2020) that a small number of principal components (PC) of factors perform well in capturing the cross-sectional variation in factor returns, to the extent that these PCs proxy for the commonality in the demand from style investing.

7 Conclusion

In this paper, I study the asset pricing implications of the style-switching demand. By introducing a top-down mechanism featuring characteristics-based trading and extrapolative belief, I show that firm-level granular styles can be defined within the characteristic space. Theoretically, stocks sharing negative (positive) correlations within the characteristic space are classified as dual (twin) styles. The switching of asset demand between these two competing styles implies cross-stock reversals for dual styles and cross-stock momentum for twin styles. Empirically, I use a set of prevalent characteristics such as value, profitability, investment, momentum, and volatility to construct dual/twin styles and find strong cross-correlation in stock returns that aligns with style switching.

My result highlights the unique role of style investing in affecting asset prices. The documented cross-reversal and cross-momentum are robust to a large set of controls and consistent with institutional trading. I further extend the analysis to the predictability of factors, where I provide evidence on both reversals and momentum in factor returns. These findings suggest that the asset management industry might in turn exert significant price impacts and contribute to market inefficiency. In future research, it would be intriguing to study the influence of style switching on other market anomalies such as the risk-return trade-off. It would also be valuable to explore the asset pricing implications of style investing in other markets such as the bond market, the derivatives market, and the foreign exchange market, as well as the potential cross-market correlations.

References

Ali, U., and D. Hirshleifer. 2020. Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics* 136:649–675.

Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets* 5:31–56.

Andonov, A., and J. D. Rauh. 2022. The return expectations of public pension funds. *The Review of Financial Studies* 35:3777–3822.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. The cross-section of volatility and expected returns. *The journal of finance* 61:259–299.

Angeletos, G.-M., Z. Huo, and K. A. Sastry. 2021. Imperfect macroeconomic expectations: Evidence and theory. *NBER Macroeconomics Annual* 35:1–86.

Anton, M., and C. Polk. 2014. Connected stocks. *The Journal of Finance* 69:1099–1127.

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

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

Avramov, D., T. Chordia, and A. Goyal. 2006. Liquidity and autocorrelations in individual stock returns. *The Journal of finance* 61:2365–2394.

Baker, M., and J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *The journal of Finance* 61:1645–1680.

Barahona, R., S. Cassella, and K. A. Jansen. 2023. Do Teams Alleviate or Exacerbate the Extrapolation Bias in the Stock Market? .

Barber, B. M., T. Odean, and N. Zhu. 2008. Do retail trades move markets? *The Review of Financial Studies* 22:151–186.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer. 2015. X-CAPM: An extrapolative capital asset pricing model. *Journal of financial economics* 115:1–24.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer. 2018. Extrapolation and bubbles. *Journal of Financial Economics* 129:203–227.

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

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

Basak, S., and A. Pavlova. 2013. Asset prices and institutional investors. *American Economic Review* 103:1728–1758.

Ben-David, I., J. Li, A. Rossi, and Y. Song. 2021. Discontinued Positive Feedback Trading and the Decline of Return Predictability. *Working paper* .

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

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

Boehmer, E., C. M. Jones, and X. Zhang. 2008. Which shorts are informed? *The Journal of Finance* 63:491–527.

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

Bollen, N. P., and R. E. Whaley. 2009. Hedge fund risk dynamics: Implications for performance appraisal. *The Journal of Finance* 64:985–1035.

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

Brennan, M. J., T. Chordia, and A. Subrahmanyam. 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of financial Economics* 49:345–373.

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

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

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

Bushee, B. J. 2001. Do institutional investors prefer near-term earnings over long-run value? *Contemporary accounting research* 18:207–246.

Bushee, B. J., and C. F. Noe. 2000. Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of accounting research* pp. 171–202.

Bybee, J. L. 2023. The Ghost in the Machine: Generating Beliefs with Large Language Models. *Working Paper* .

Campbell, J. Y., S. J. Grossman, and J. Wang. 1993. Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics* 108:905–939.

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

Chabakauri, G., and O. Rytchkov. 2021. Asset pricing with index investing. *Journal of Financial Economics* 141:195–216.

Chen, A., G. Hoberg, and M. B. Zhang. 2022. Wisdom of the Institutional Crowd: Implications for Anomaly Returns. *Available at SSRN* .

Chen, A. Y., and J. McCoy. 2022. Missing values and the dimensionality of expected returns. *arXiv preprint arXiv:2207.13071* .

Chen, A. Y., and T. Zimmermann. 2021. Open source cross-sectional asset pricing. *Critical Finance Review, Forthcoming* .

Chen, H.-l. 2003. On characteristics momentum. *The Journal of Behavioral Finance* 4:137–156.

Chen, X., L. An, Z. Wang, and J. Yu. 2023. Attention spillover in asset pricing. *The Journal of*

Finance 78:3515–3559.

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

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

Clarke, C., and M. Linn. 2022. Characteristics and the Cross-Section of Covariances. *Available at SSRN 3141622* .

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

Cohen, L., and D. Lou. 2012. Complicated firms. *Journal of financial economics* 104:383–400.

Cosemans, M., and R. Frehen. 2021. Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics* 140:460–483.

Coval, J., and E. Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86:479–512.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *The journal of finance* 66:1461–1499.

Da, Z., J. Hua, C.-C. Hung, and L. Peng. 2023. Market returns and a tale of two types of attention. *Available at SSRN 3551662* .

Da, Z., X. Huang, and L. J. Jin. 2021. Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics* 140:175–196.

Dai, W., M. Medhat, R. Novy-Marx, and S. Rizova. 2023. Reversals and the returns to liquidity provision. *NBER Working Paper* .

Daniel, K., L. Mota, S. Rottke, and T. Santos. 2020. The cross-section of risk and returns. *The Review of Financial Studies* 33:1927–1979.

Daniel, K., and S. Titman. 1997. Evidence on the characteristics of cross sectional variation in stock returns. *the Journal of Finance* 52:1–33.

Daniel, K., S. Titman, et al. 1998. Characteristics or covariances. *Journal of Portfolio Management* 24:24–33.

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

Deng, Y. 2021. Extrapolative expectations, corporate activities, and asset prices. *Working paper* .

Dong, X., and C. Yang. 2023. Anomalies Never Disappeared: The Case of Stubborn Retail Investors. *Available at SSRN 4417278* .

Drake, M. S., L. Rees, and E. P. Swanson. 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. *The Accounting Review* 86:101–130.

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

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

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

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

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

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

Fung, W., and D. A. Hsieh. 1997. Empirical characteristics of dynamic trading strategies: The case of hedge funds. *The review of financial studies* 10:275–302.

Gabaix, X., and R. S. Koijen. 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Tech. rep., National Bureau of Economic Research.

Gennaioli, N., Y. Ma, and A. Shleifer. 2016. Expectations and investment. *NBER Macroeconomics Annual* 30:379–431.

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

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

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

Greenwood, R., and A. Shleifer. 2014. Expectations of returns and expected returns. *The Review of Financial Studies* 27:714–746.

Greenwood, R., and D. Thesmar. 2011. Stock price fragility. *Journal of Financial Economics* 102:471–490.

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

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

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

He, W., H. Wang, Y. Wang, and J. Yu. 2023. Similar Stocks. *Available at SSRN 3815595* .

Hoberg, G., and G. M. Phillips. 2018. Text-based industry momentum. *Journal of Financial and Quantitative Analysis* 53:2355–2388.

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

Hou, K. 2007. Industry information diffusion and the lead-lag effect in stock returns. *The review of* *financial studies* 20:1113–1138.

Hou, K., H. Mo, C. Xue, and L. Zhang. 2021. An augmented q-factor model with expected growth. *Review of Finance* 25:1–41.

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

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

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

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

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *The Journal of finance* 45:881–898.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance* 48:65–91.

Jiang, G. J., B. Liang, and H. Zhang. 2022. Hedge fund manager skill and style-shifting. *Management Science* 68:2284–2307.

Kashyap, A. K., N. Kovrijnykh, J. Li, and A. Pavlova. 2023. Is there too much benchmarking in asset management? *American Economic Review* 113:1112–1141.

Kaul, G., and M. Nimalendran. 1990. Price reversals: Bid-ask errors or market overreaction? *Journal of Financial Economics* 28:67–93.

Kelly, B., S. Malamud, and L. H. Pedersen. 2023. Principal portfolios. *The Journal of Finance* 78:347–387.

Kim, B. 2022. Correlated Demand Shocks and Asset Pricing. *Working paper* .

Koch, A., S. Ruenzi, and L. Starks. 2016. Commonality in liquidity: a demand-side explanation. *The Review of Financial Studies* 29:1943–1974.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132:665–712.

Koijen, R. S., R. J. Richmond, and M. Yogo. 2023. Which investors matter for equity valuations and expected returns? *Review of Economic Studies* p. rdad083.

Koijen, R. S., and M. Yogo. 2019. A demand system approach to asset pricing. *Journal of Political Economy* 127:1475–1515.

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

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

La Porta, R. 1996. Expectations and the cross-section of stock returns. *The Journal of Finance* 51:1715–1742.

Lee, C. M., S. T. Sun, R. Wang, and R. Zhang. 2019. Technological links and predictable returns. *Journal of Financial Economics* 132:76–96.

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

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

Lewellen, J., and J. Shanken. 2002. Learning, asset-pricing tests, and market efficiency. *The Journal of finance* 57:1113–1145.

Liao, J., C. Peng, and N. Zhu. 2022. Extrapolative bubbles and trading volume. *The Review of Financial Studies* 35:1682–1722.

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

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

McLean, R. D., J. Pontiff, and C. Reilly. 2020. Taking sides on return predictability. *Available at SSRN 3637649* .

Menzly, L., and O. Ozbas. 2010. Market segmentation and cross-predictability of returns. *The Journal of Finance* 65:1555–1580.

Moskowitz, T. J., and M. Grinblatt. 1999. Do industries explain momentum? *The Journal of finance* 54:1249–1290.

Nagel, S. 2012. Evaporating liquidity. *The Review of Financial Studies* 25:2005–2039.

Pan, W., Z. Su, H. Wang, and J. Yu. 2021. Extrapolative market participation. *Available at SSRN 3830569* .

Parsons, C. A., R. Sabbatucci, and S. Titman. 2020. Geographic lead-lag effects. *The Review of Financial Studies* 33:4721–4770.

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

Peng, C., and C. Wang. 2023. Factor demand and factor returns. *Available at SSRN 3327849* .

Peng, L., and W. Xiong. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80:563–602.

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

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

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The short of it: Investor sentiment and anomalies. *Journal of financial economics* 104:288–302.

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

Vayanos, D., and P. Woolley. 2013. An institutional theory of momentum and reversal. *The Review of Financial Studies* 26:1087–1145.

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

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

Yan, J., and J. Yu. 2023. Cross-stock momentum and factor momentum. *Journal of Financial Economics* 150:103716.

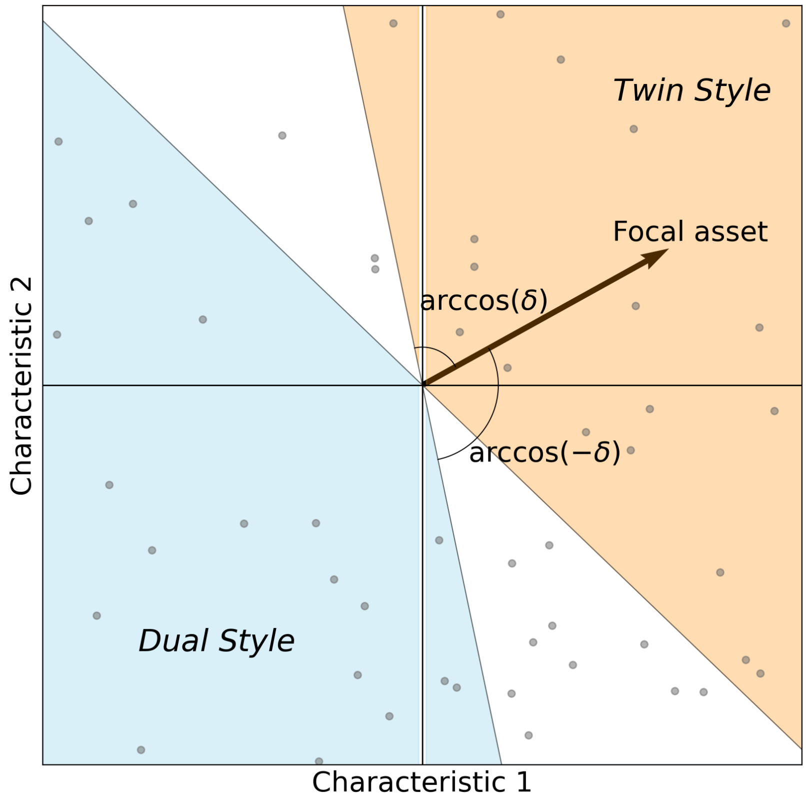

Figure 1. Dual and twin styles.
This figure illustrates the concept of dual and twin styles within a two-dimensional characteristic space. For any given focal asset, assets located within the orange region are classified as twin styles, while those situated within the blue region are identified as dual styles. The parameter $\delta \in [0, 1)$ balances between the precision and inclusiveness of the empirical construction. The term *arccos* represents the inverse cosine function.

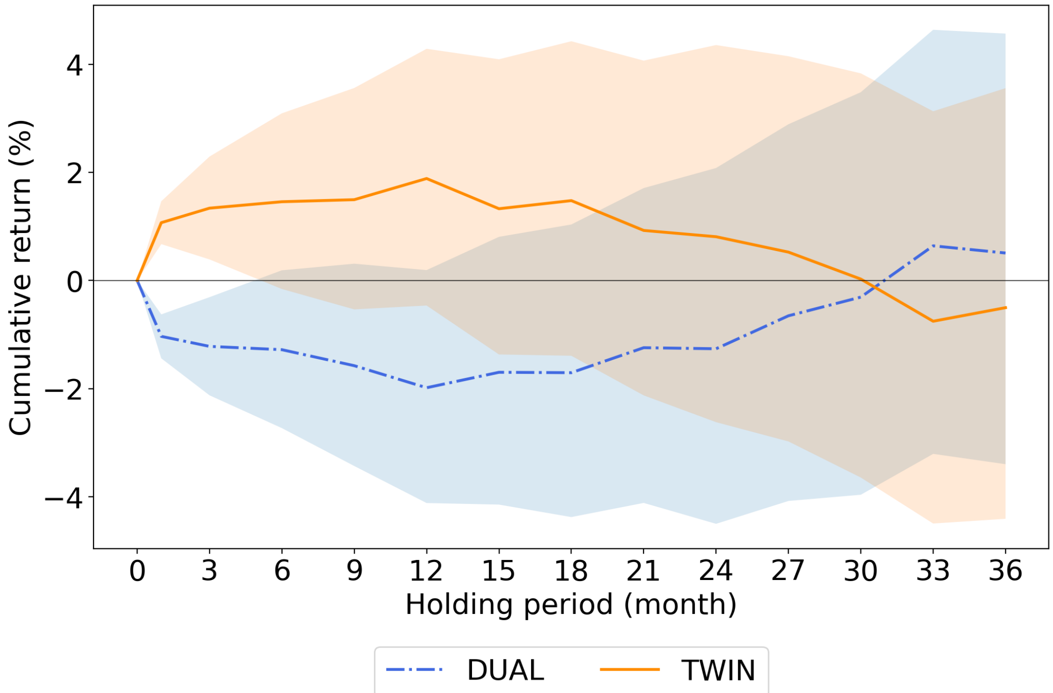

Figure 2. Long-term performance of DUAL and TWIN style strategies.
This figure plots the average cumulative returns of high-minus-low portfolios based on DUAL (dashed blue line) and TWIN (solid orange line). Strategy returns are market adjusted using CAPM. The shaded areas represent the 95% confidence intervals. The sample period is from July 1963 to December 2021.

Table 1. Summary statistics of dual- and twin-style portfolios.
This table reports summary statistics of portfolios formed on dual-style returns (Panel A) and twin-style returns (Panel B). At the end of June each year, stocks are represented as vectors in a five-dimensional characteristic space comprising value, profitability, investment, volatility, and momentum. Stock-specific dual and twin styles are identified using cosine similarities between these characteristic vectors. For each stock, DUAL (TWIN) is the value-weighted monthly return of other stocks within the dual (twin) style. Each month, I sort stocks into quintile portfolios based on DUAL and TWIN, respectively, and calculate equal-weighted averages of firm characteristics within each portfolio. The table shows for each DUAL/TWIN quintile the time-series average of monthly characteristics. RET is the focal stock's (contemporaneous) monthly return. BM is the book-to-market ratio. OPe is operating profit. AG is asset growth. MOM is the cumulative 11-month return (skipping the most recent month). VOL is the standard deviation of monthly returns over the past five years. IVol is the idiosyncratic volatility (Ang et al., 2006). SIZE is the log of market capitalization. ILLIQ is the illiquidity measure of Amihud (2002) with a one-month calculation window. ST is the salience theory value, calculated using daily returns in a month (Cosemans and Frehen, 2021). DUAL, TWIN, RET, MOM, IVol, and ST are presented in percentages. The sample period is from July 1963 to December 2021.

Panel A. DUAL portfolios

	DUAL	RET	BM	OPe	AG	MOM	VOL	IVol	Size	ILLIQ	ST
Low	-0.72	3.75	0.84	-0.17	0.18	0.14	2.45	21.13	12.08	0.48	0.82
2	0.41	3.01	0.98	0.02	0.17	0.15	2.66	18.44	11.75	0.70	0.85
3	1.96	1.46	0.95	0.08	0.17	0.14	2.48	16.06	11.84	0.60	0.62
4	3.66	0.04	0.84	0.18	1.20	0.13	2.31	15.03	12.14	0.52	0.44
High	5.17	-0.55	0.72	-0.02	0.17	0.12	2.03	14.51	12.58	0.34	0.26
High-Low	5.88	-4.30	-0.12	0.16	-0.01	-0.03	-0.42	-6.62	0.50	-0.14	-0.56

Panel B. TWIN portfolios

	TWIN	RET	BM	OPe	AG	MOM	VOL	IVol	Size	ILLIQ	ST
Low	-0.46	-0.03	0.93	-0.23	0.21	0.15	2.61	15.71	11.65	0.66	0.57
2	0.71	0.10	0.76	0.24	1.18	0.12	2.07	14.79	12.52	0.37	0.34
3	1.52	1.39	0.75	0.32	0.14	0.10	1.89	14.68	12.81	0.30	0.36
4	2.68	2.81	0.85	0.09	0.17	0.13	2.37	17.57	12.14	0.50	0.69
High	4.52	3.46	1.03	-0.36	0.20	0.17	2.97	22.42	11.29	0.81	1.03
High-Low	4.98	3.48	0.10	-0.13	-0.01	0.02	0.36	6.72	-0.35	0.15	0.46

Table 2. One-sort portfolios based on dual- and twin-style returns.
This table reports portfolio returns based on DUAL (Panel A) and TWIN (Panel B), and the sum of two strategy returns (Panel C). For each stock, DUAL (TWIN) is the value-weighted monthly return of other stocks sharing negative (positive) cosine similarities within the characteristic space, defined according to equation (11). Each month, stocks are sorted into quintile portfolios based on DUAL (Panel A) or TWIN (Panel B). The table presents value-weighted monthly returns for quintile portfolios, as well as value-weighted (VW) and equal-weighted (EW) monthly returns for the high-minus-low hedge strategy. Panel C reports the sum of long-short strategies. Returns are reported using the raw excess return (Return) and factor-adjusted returns, including the Fama and French (1996) model (FF3), the Carhart (1997) model (Carhart), the Fama and French (2015) model (FF5), the momentum-augmented model (FF6), the momentum and short-term reversal-augmented model (FF6+Rev), the q-factor (Hou et al., 2015) model (Q4), and the expected growth-augmented q-factor (Hou et al., 2021) model (Q5). The sample period is from July 1963 to December 2021. The t-statistics with Newey-West adjusted standard errors are shown in parentheses.

Quintile	Return	FF3	Carhart	FF5	FF6	FF6+Rev	Q4	Q5
Panel A. Dual styles								
Low	1.254	0.597	0.568	0.630	0.604	0.937	0.705	0.584
	(4.83)	(4.21)	(4.10)	(3.76)	(3.99)	(6.58)	(3.61)	(3.12)
2	1.079	0.442	0.447	0.473	0.475	0.707	0.561	0.500
	(4.56)	(4.73)	(4.87)	(4.29)	(4.60)	(7.39)	(4.26)	(3.20)
3	0.771	0.174	0.146	0.194	0.169	0.240	0.212	0.214
	(3.80)	(2.28)	(1.96)	(2.29)	(2.13)	(2.54)	(2.14)	(2.15)
4	0.485	-0.163	-0.127	-0.126	-0.099	-0.285	-0.111	-0.033
	(2.32)	(-1.85)	(-1.37)	(-1.39)	(-1.05)	(-3.19)	(-1.07)	(-0.30)
High	0.254	-0.420	-0.333	-0.389	-0.318	-0.573	-0.371	-0.300
	(1.21)	(-4.28)	(-3.43)	(-3.60)	(-3.12)	(-6.09)	(-3.05)	(-2.36)
High-Low	-1.000	-1.017	-0.901	-1.019	-0.922	-1.510	-1.076	-0.884
(VW)	(-4.60)	(-4.81)	(-4.37)	(-4.01)	(-4.06)	(-7.72)	(-3.64)	(-2.99)
High-Low	-1.202	-1.148	-1.121	-1.167	-1.144	-1.596	-1.245	-1.142
(EW)	(-6.06)	(-6.27)	(-6.07)	(-5.76)	(-5.83)	(-8.77)	(-5.34)	(-4.51)
Panel B. Twin styles								
Low	0.154	-0.658	-0.562	-0.602	-0.526	-0.813	-0.503	-0.463
	(0.61)	(-5.57)	(-5.09)	(-4.27)	(-4.22)	(-6.29)	(-3.30)	(-2.80)
2	0.372	-0.262	-0.227	-0.232	-0.205	-0.415	-0.211	-0.151
	(1.86)	(-2.89)	(-2.46)	(-2.42)	(-2.21)	(-4.86)	(-1.92)	(-1.27)
3	0.667	0.146	0.126	0.088	0.076	0.103	0.074	0.062
	(3.96)	(3.16)	(2.78)	(1.69)	(1.60)	(2.04)	(1.29)	(0.98)
4	0.976	0.366	0.378	0.423	0.429	0.688	0.516	0.465
	(4.14)	(3.28)	(3.62)	(3.28)	(3.68)	(5.48)	(3.35)	(3.01)
High	1.173	0.365	0.425	0.473	0.516	0.760	0.622	0.519
	(4.38)	(2.89)	(3.48)	(3.93)	(4.32)	(6.34)	(4.33)	(3.58)
High-Low	1.020	1.023	0.987	1.075	1.042	1.573	1.125	0.983
(VW)	(4.92)	(4.97)	(5.16)	(4.63)	(4.96)	(7.36)	(4.23)	(3.54)
High-Low	1.109	1.067	1.036	1.087	1.061	1.437	1.122	1.080
(EW)	(6.04)	(6.13)	(6.04)	(5.74)	(5.80)	(8.47)	(5.01)	(4.41)
Panel C. Dual + Twin								
VW	0.019	0.006	0.086	0.056	0.120	0.063	0.049	0.099
	(0.16)	(0.05)	(0.65)	(0.48)	(0.97)	(0.49)	(0.38)	(0.65)
EW	-0.093	-0.080	-0.084	-0.080	-0.083	-0.159	-0.123	-0.062
	(-1.48)	(-1.31)	(-1.20)	(-1.18)	(-1.11)	(-2.31)	(-1.57)	(-0.75)

Table 3. One-sort portfolios based on residual dual- and twin-style returns. This table reports portfolio returns based on residual DUAL (Panel A) and residual TWIN (Panel B). Residual DUAL (TWIN) is calculated as the residual from cross-sectional regressions of DUAL (TWIN) on TWIN (DUAL). For each stock, DUAL (TWIN) is the value-weighted monthly return of other stocks sharing negative (positive) cosine similarities within the characteristic space, defined according to equation (11). Each month, stocks are sorted into quintile portfolios based on residual DUAL (Panel A) or residual TWIN (Panel B). The table presents value-weighted monthly returns for quintile portfolios, as well as value-weighted (VW) and equal-weighted (EW) monthly returns for the high-minus-low hedge strategy. Panel C reports the sum of long-short strategies. Returns are reported using the raw excess return (Return) and factor-adjusted returns, including the Fama and French (1996) model (FF3), the Carhart (1997) model (Carhart), the Fama and French (2015) model (FF5), the momentum-augmented model (FF6), the momentum and short-term reversal-augmented model (FF6+Rev), the q-factor (Hou et al., 2015) model (Q4), and the expected growth-augmented q-factor (Hou et al., 2021) model (Q5). The sample period is from July 1963 to December 2021. The t-statistics with Newey-West adjusted standard errors are shown in parentheses.

Quintile	Return	FF3	Carhart	FF5	FF6	FF6+Rev	Q4	Q5
Panel A. Residual dual styles								
Low	1.074	0.466	0.422	0.476	0.438	0.699	0.537	0.447
	(4.73)	(4.34)	(3.94)	(3.67)	(3.72)	(6.47)	(3.49)	(2.71)
2	0.894	0.293	0.289	0.253	0.254	0.420	0.325	0.245
	(4.33)	(3.95)	(3.85)	(2.97)	(3.26)	(5.14)	(3.12)	(1.86)
3	0.678	0.106	0.131	0.161	0.178	0.242	0.203	0.227
	(3.52)	(1.71)	(2.21)	(2.33)	(2.70)	(3.11)	(2.59)	(2.88)
4	0.528	-0.063	-0.070	-0.103	-0.106	-0.221	-0.082	-0.086
	(2.89)	(-0.86)	(-0.99)	(-1.34)	(-1.34)	(-3.02)	(-0.99)	(-1.02)
High	0.411	-0.212	-0.131	-0.220	-0.151	-0.350	-0.203	-0.146
	(2.20)	(-2.65)	(-1.72)	(-2.45)	(-1.82)	(-4.57)	(-1.92)	(-1.41)
High-Low	-0.663	-0.677	-0.553	-0.696	-0.589	-1.049	-0.739	-0.594
(VW)	(-3.94)	(-4.10)	(-3.49)	(-3.44)	(-3.32)	(-6.89)	(-3.12)	(-2.39)
High-Low	-0.706	-0.669	-0.641	-0.683	-0.659	-0.868	-0.729	-0.681
(EW)	(-6.58)	(-6.53)	(-6.20)	(-6.01)	(-6.06)	(-8.21)	(-5.89)	(-5.18)
Panel B. Residual twin styles								
Low	0.696	0.044	0.028	0.120	0.101	0.232	0.190	0.086
	(2.84)	(0.36)	(0.23)	(1.09)	(0.87)	(2.03)	(1.27)	(0.56)
2	0.776	0.229	0.205	0.229	0.209	0.323	0.242	0.231
	(4.36)	(3.65)	(3.30)	(3.36)	(3.27)	(4.98)	(3.27)	(3.47)
3	0.626	0.079	0.089	0.002	0.017	0.021	0.026	0.007
	(3.77)	(1.58)	(1.48)	(0.03)	(0.28)	(0.32)	(0.39)	(0.11)
4	0.528	-0.022	-0.004	-0.056	-0.037	-0.104	-0.015	-0.048
	(3.10)	(-0.37)	(-0.06)	(-0.89)	(-0.60)	(-1.66)	(-0.24)	(-0.77)
High	0.543	-0.130	-0.050	-0.108	-0.042	-0.183	-0.014	-0.060
	(2.58)	(-1.52)	(-0.55)	(-1.23)	(-0.44)	(-1.70)	(-0.13)	(-0.61)
High-Low	-0.153	-0.174	-0.079	-0.229	-0.143	-0.415	-0.204	-0.147
(VW)	(-1.06)	(-1.23)	(-0.53)	(-1.62)	(-1.00)	(-3.00)	(-1.18)	(-0.79)
High-Low	0.539	0.539	0.514	0.538	0.519	0.676	0.552	0.534
(EW)	(5.01)	(4.86)	(4.64)	(4.24)	(4.15)	(5.75)	(3.64)	(3.42)

Table 4. Fama-MacBeth regressions using dual and twin style returns.
This table reports time-series averages of coefficients from monthly cross-sectional regressions. The dependent variable is the focal stock's future monthly return (multiplied by 100) and the main independent variables of interest are DUAL and TWIN. For each stock, DUAL (TWIN) is the value-weighted monthly return of other stocks within the dual (twin) style, which is identified using cosine similarities between characteristic vectors. Industry return (INDRET) is the value-weighted average return of other stocks within the same two-digit SIC code industry. Style return (STYRET) is the value-weighted average return of other stocks within the same BM-Size groups (Wahal and Yavuz, 2013). Connected-firm return (CFRET) is the shared analyst coverage return (Ali and Hirshleifer, 2020). Other control variables include the book-to-market ratio (BM), asset growth (AG), operating profits (OPe), momentum (MOM), idiosyncratic volatility (IVol), monthly stock return (RET), firm size (SIZE), illiquidity (ILLIQ), and the salience theory value (ST). Independent variables are cross-sectionally winsorized at the 1% and 99% levels and standardized to have zero mean and unit variance. The sample period is from July 1963 to December 2021 except for regressions with CFRET, where the sample period is from January 1984 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DUAL	-0.244	-0.213	-0.237	-0.148	-0.144					
	(-5.25)	(-4.72)	(-5.18)	(-2.83)	(-2.78)					
TWIN						0.191	0.192	0.185	0.136	0.139
						(4.73)	(4.78)	(4.63)	(2.73)	(2.77)
INDRET		0.371			0.145		0.380			0.146
		(10.28)			(3.97)		(10.27)			(3.91)
STYRET			0.030		-0.038			0.062		-0.024
			(1.18)		(-1.18)			(2.19)		(-0.68)
CFRET				0.538	0.462				0.540	0.463
				(7.14)	(6.81)				(7.08)	(6.79)
BM	0.128	0.132	0.097	0.047	0.007	0.123	0.126	0.093	0.037	-0.001
	(2.87)	(3.02)	(2.21)	(0.76)	(0.12)	(2.76)	(2.89)	(2.12)	(0.58)	(-0.01)
AG	-0.322	-0.329	-0.318	-0.366	-0.376	-0.312	-0.321	-0.308	-0.357	-0.366
	(-7.65)	(-7.29)	(-7.58)	(-6.94)	(-6.54)	(-7.36)	(-7.04)	(-7.30)	(-6.73)	(-6.31)
OPe	0.193	0.187	0.186	0.165	0.151	0.197	0.193	0.191	0.160	0.148
	(5.01)	(4.92)	(4.87)	(2.87)	(2.59)	(5.25)	(5.19)	(5.15)	(2.88)	(2.61)
MOM	0.275	0.256	0.283	0.244	0.259	0.284	0.261	0.292	0.259	0.270
	(4.54)	(4.27)	(4.73)	(3.06)	(3.27)	(4.57)	(4.29)	(4.79)	(3.21)	(3.39)
IVol	-0.198	-0.200	-0.194	-0.330	-0.330	-0.185	-0.189	-0.180	-0.316	-0.313
	(-3.16)	(-3.14)	(-3.09)	(-4.12)	(-3.98)	(-2.87)	(-2.90)	(-2.80)	(-3.89)	(-3.72)
RET	-0.625	-0.705	-0.626	-0.606	-0.617	-0.615	-0.697	-0.619	-0.604	-0.617
	(-9.86)	(-11.0)	(-9.82)	(-7.81)	(-8.03)	(-9.78)	(-11.0)	(-9.79)	(-7.86)	(-8.07)
SIZE	-0.198	-0.184	-0.208	-0.169	-0.201	-0.212	-0.196	-0.214	-0.179	-0.207
	(-4.12)	(-3.93)	(-4.20)	(-2.92)	(-3.07)	(-4.31)	(-4.16)	(-4.32)	(-3.00)	(-3.15)
ILLIQ	-0.095	-0.032	-0.106	-0.087	-0.190	-0.085	-0.017	-0.099	-0.097	-0.205
	(-0.82)	(-0.28)	(-0.91)	(-0.97)	(-1.38)	(-0.78)	(-0.16)	(-0.88)	(-1.10)	(-1.48)
ST	-0.021	-0.002	-0.022	0.105	0.107	-0.022	-0.003	-0.023	0.103	0.107
	(-0.63)	(-0.07)	(-0.68)	(2.48)	(2.51)	(-0.65)	(-0.10)	(-0.69)	(2.46)	(2.52)
Avg. R^2(%)	5.831	6.224	5.903	5.706	6.039	5.766	6.170	5.854	5.708	6.049
Avg. # Obs	2346	2304	2346	2130	2080	2346	2304	2346	2130	2080

Table 5. Macroeconomic conditions and style strategy performance.
This table reports time-series regressions of dual- and twin-style strategy returns on lagged macroeconomic risk variables:

$$R_{style,t+1} = a + bMacro_t + cMKT_{t+1} + \varepsilon_{style,t+1}.$$

The dependent variable $R_{style,t+1}$ is the monthly value-weighted strategy return based on dual or twin styles. $Macro_t$ is the lagged macro-related variable, including the book-to-market ratio (BM), dividend-price ratio (DP), earnings-price ratio (EP), default yield spread (DFY), term spread (TMS), stock variance (SVAR), inflation (INFL), net equity expansion (NTIS), cross-sectional premium (CSP), and the trend deviation of consumption to asset wealth and labor income (CAY). Since the original CAY is updated quarterly, I use the most recent quarterly CAY to convert the data to the monthly frequency. I also control for the contemporaneous market excess return (MKT_{t+1}) in regressions. Independent variables are standardized to have zero mean and unit variance. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Dual style		Twin style	
	b (Macro)	c (MKT)	b (Macro)	c (MKT)
BM	0.114	0.282	0.071	-0.394
	(0.46)	(0.98)	(0.30)	(-1.43)
DP	0.040	0.281	0.083	-0.396
	(0.15)	(0.97)	(0.33)	(-1.44)
EP	0.382	0.275	-0.128	-0.391
	(1.57)	(0.97)	(-0.58)	(-1.43)
DFY	-0.173	0.292	0.122	-0.401
	(-0.76)	(1.02)	(0.58)	(-1.46)
TMS	-0.147	0.292	-0.002	-0.394
	(-0.79)	(1.00)	(-0.01)	(-1.42)
SVAR	-0.189	0.280	-0.029	-0.394
	(-0.73)	(0.97)	(-0.15)	(-1.43)
INFL	0.189	0.298	-0.076	-0.400
	(1.03)	(1.03)	(-0.43)	(-1.44)
NTIS	-0.284	0.271	0.266	-0.383
	(-1.39)	(0.93)	(1.44)	(-1.38)
CSP	-0.227	0.350	0.499	-0.572
	(-0.87)	(1.07)	(2.12)	(-1.70)
CAY	0.029	0.281	-0.028	-0.393
	(0.13)	(0.97)	(-0.13)	(-1.42)

Table 6. Institutional trading on dual and twin styles.
This table reports panel regressions of institutional investors' trading on dual- and twin-style returns:

$$\Delta Inst_{i,t+1} = a + b_{style} Style_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable ($\Delta Inst_{i,t+1}$, multiplied by 100) is the quarterly change in institutional ownership in Panel A and the percentage change in the number of institutional investors holding the stock in Panel B. Institutional ownership is the ratio between shares held by institutional investors and the total shares outstanding. DUAL (TWIN) is the lagged cumulative return of dual (twin) style stocks in the past three months. Control variables include the log of market capitalization, the log of the book-to-market ratio, the focal stock's past 3-month return and past 11-month return (skipping the most recent month), asset growth, operating profits, and return volatility. All variables are winsorized at 1% and 99% each quarter. Independent variables are cross-sectionally standardized to have zero mean and unit variance. Regressions feature quarter and industry fixed effects. The t-statistics based on standard errors clustered at quarter and firm levels are reported in parentheses. The sample period is from June 1980 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in the institutional ownership						
DUAL	-0.072	-0.072			-0.047	-0.048
	(-3.12)	(-3.14)			(-2.33)	(-2.37)
TWIN			0.070	0.070	0.042	0.042
			(3.27)	(3.27)	(2.44)	(2.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
N	453295	453287	453295	453287	453295	453287
Adj. R^2	0.09	0.09	0.09	0.09	0.09	0.09
Panel B. Change in the number of institutional investors						
DUAL	-0.436	-0.438			-0.249	-0.255
	(-4.13)	(-4.16)			(-2.88)	(-2.96)
TWIN			0.467	0.464	0.318	0.312
			(4.23)	(4.21)	(3.36)	(3.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes
N	453295	453287	453295	453287	453295	453287
Adj. R^2	0.09	0.09	0.09	0.09	0.09	0.09

Table 7. Trading of different types of institutional investors.
This table reports panel regressions of institutional investors' trading on dual- and twin-style returns, where institutions are classified based on the *Institutional Investor Classification* of Brian Bushee:

$$\Delta Inst_{i,t+1}^{class} = a + b_{style} Style_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}.$$

The classification includes bank trust (BNK), insurance company (INS), investment company (INV), independent investment advisor (IIA), pension fund (PSF), and others (OTHER). In particular, pension fund ownership is the sum of ownership of corporate (private) pension fund and public pension fund; institutions labeled as university and foundation endowments or miscellaneous, or institutions with missing labels are classified as OTHER. The dependent variable (multiplied by 100) is the quarterly change in institutional ownership. DUAL (TWIN) is the lagged cumulative return of dual (twin) style stocks in the past three months. Control variables include the log of market capitalization, the log of the book-to-market ratio, the focal stock's past 3-month return and past 11-month return (skipping the most recent month), asset growth, operating profits, and return volatility. All variables are winsorized at 1% and 99% each quarter. Independent variables are cross-sectionally standardized to have zero mean and unit variance. Regressions feature quarter and industry fixed effects. The t-statistics based on standard errors clustered at quarter and firm levels are reported in parentheses. The sample period is from June 1980 to December 2021.

	BNK		INS		INV		IIA		PSF		OTHER	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DUAL	0.001		-0.005		-0.009		-0.053		0.005		-0.007	
	(0.09)		(-1.08)		(-1.52)		(-2.93)		(1.09)		(-0.58)	
TWIN		0.003		0.006		0.008		0.057		-0.002		0.000
		(0.32)		(1.37)		(1.41)		(3.45)		(-0.53)		(0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	437206	437206	398183	398183	395425	395425	436699	436699	382268	382268	406637	406637
Adj. R^2	0.16	0.16	0.03	0.03	0.02	0.02	0.11	0.11	0.10	0.10	0.38	0.38

Table 8. Style trading of short sellers and retail investors.
This table reports the trading by short sellers and retail investors over h months after style portfolio formation. Short seller trading is measured as the change in monthly short interest ratios, where the short interest ratio is defined as month-end short interest divided by shares outstanding. A positive value of short seller trading indicates an increase in short interest and vice versa. Monthly retail trading is calculated by summing the daily percentage of shares purchased by retail investors, which is defined as retail buys volume minus retail sells volume, scaled by shares outstanding. Daily retail trading volume data are extracted from WRDS - TAQ Millisecond Tools, where retail trades are identified through the Boehmer et al. (2021) algorithm. At the end of each month, stocks are sorted into three portfolios based on the dual-style return or the twin-style return. The high group consists of stocks with style returns above the 70th percentile, while the low group consists of stocks with returns below the 30th percentile. The table presents value-weighted average trading measures of each portfolio over the subsequent h months using the methodology of Jegadeesh and Titman (1993). Specifically, for portfolios with a holding period of h months, each group consists of h subgroups, which are separately initiated in the previous h months. These subgroups represent value-weighted average trading measures. The portfolios are formed by equally weighting these h subgroups. Also reported is the difference between the high and the low portfolios. The t-statistics with Newey-West adjusted standard errors are shown in parentheses. The sample period is from January 1973 to December 2021 for Panel A and Panel B, and from January 2007 to December 2021 for Panel C and Panel D.

	Holding period (months)							
	1	3	6	12	18	24	30	36
Panel A. Short seller trading: Dual styles								
Low	-1.595	-1.251	-0.537	-0.267	-0.147	-0.144	-0.099	-0.053
Medium	-0.176	-0.145	0.015	0.148	0.175	0.253	0.263	0.222
High	0.180	0.225	0.363	0.313	0.187	0.150	0.116	0.138
High-Low	1.775	1.476	0.900	0.580	0.334	0.293	0.214	0.191
	(2.62)	(3.07)	(2.64)	(2.51)	(1.71)	(1.57)	(1.32)	(1.13)
Panel B. Short seller trading: Twin styles								
Low	-0.038	0.011	0.089	0.141	0.069	0.031	0.016	0.033
Medium	0.086	0.127	0.250	0.292	0.306	0.338	0.340	0.327
High	-1.581	-1.094	-0.631	-0.345	-0.219	-0.205	-0.231	-0.196
High-Low	-1.544	-1.104	-0.720	-0.487	-0.288	-0.236	-0.247	-0.228
	(-2.35)	(-2.28)	(-2.02)	(-1.84)	(-1.30)	(-1.17)	(-1.49)	(-1.34)

(*Continued*)

	Holding period (months)							
	1	3	6	12	18	24	30	36
Panel C. Retail trading: Dual styles								
Low	0.432	0.463	0.444	0.488	0.455	0.513	0.449	0.575
Medium	-0.223	-0.160	-0.114	-0.067	-0.073	-0.041	-0.093	-0.012
High	0.111	0.092	0.148	0.211	0.179	0.211	0.097	0.194
High-Low	-0.321	-0.371	-0.296	-0.276	-0.277	-0.303	-0.352	-0.381
	(-0.88)	(-1.24)	(-1.16)	(-1.44)	(-1.72)	(-2.43)	(-3.57)	(-4.18)
Panel D. Retail trading: Twin styles								
Low	0.507	0.526	0.563	0.622	0.607	0.605	0.526	0.579
Medium	-0.426	-0.361	-0.293	-0.260	-0.255	-0.231	-0.347	-0.275
High	1.114	1.047	1.015	1.002	0.928	0.987	0.940	1.040
High-Low	0.606	0.521	0.452	0.380	0.321	0.382	0.414	0.461
	(1.60)	(1.41)	(1.53)	(1.61)	(1.60)	(2.35)	(2.92)	(3.73)

Table 9. Institutional attention and style returns.
This table reports the time variation in style strategy returns in response to aggregate institutional investor attention (AIA). Panel A investigates the abnormal returns following high- and low-AIA periods based on regression

$$R_{style,t+1} = \alpha_H \mathbf{I}_{\text{High},t} + \alpha_L \mathbf{I}_{\text{Low},t} + c' Factors_{t+1} + \varepsilon_{style,t+1},$$

where $\mathbf{I}_{\text{High},t}$ and $\mathbf{I}_{\text{Low},t}$ are dummy variables indicating high- and low-AIA periods, $R_{style,t+1}$ is the subsequent strategy return based on dual or twin styles, and $Factors_{t+1}$ is the vector of asset pricing factors. Also reported is the difference between α_H and α_L (High-Low). Panel B reports the result from regression

$$R_{style,t+1} = a + b_1 AIA_t + b_2 ARA_t + b_3 SENT_t + c' Controls_{t+1} + \varepsilon_{style,t+1},$$

where AIA_t is the aggregate institutional investor attention, ARA_t is the aggregate retail investor attention, and $SENT_t$ is the investor sentiment index of Baker and Wurgler (2006). $Controls_{t+1}$ is the vector of control variables, including the six asset pricing factors of Fama and French (2015). For ease of interpretation, AIA, ARA, and SENT are standardized to have zero mean and unit variance. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses. Constrained by data availability, the sample period differs across specifications. In Panel A, the sample period spans from March 2010 to December 2021. In Panel B, the sample period encompasses March 2010 to December 2021 for columns (1) and (2), May 2004 to December 2020 for columns (3) and (4), and March 2010 to December 2020 for columns (5) and (6).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. High- and low-AIA periods						
	Dual style			Twin style		
	High AIA	Low AIA	High-Low	High AIA	Low AIA	High-Low
CAPM	-1.172	0.047	-1.219	0.693	-0.320	1.013
	(-2.81)	(0.10)	(-2.26)	(1.30)	(-0.80)	(1.60)
FF3	-1.280	0.010	-1.29	0.862	-0.257	1.119
	(-2.84)	(0.02)	(-2.33)	(1.51)	(-0.61)	(1.67)
Carhart	-1.416	-0.013	-1.403	0.992	-0.235	1.227
	(-2.98)	(-0.03)	(-2.60)	(1.69)	(-0.59)	(1.82)
FF5	-1.165	0.041	-1.206	0.973	-0.241	1.214
	(-2.64)	(0.09)	(-2.11)	(1.93)	(-0.56)	(1.92)
FF6	-1.319	0.016	-1.335	1.120	-0.217	1.337
	(-2.86)	(0.04)	(-2.43)	(2.17)	(-0.54)	(2.14)
Panel B. Predictive regressions						
	Dual style			Twin style		
AIA	-0.658		-0.774	0.381		0.643
	(-2.26)		(-2.53)	(1.37)		(2.10)
ARA		-0.327	0.083		-0.117	-0.481
		(-0.92)	(0.21)		(-0.42)	(-1.28)
SENT	-0.750	0.419	-1.425	-0.847	0.355	-0.792
	(-0.97)	(0.35)	(-0.45)	(-0.97)	(0.28)	(-0.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	142	200	130	142	200	130

Table 10. Spanning tests.

This table reports the results from spanning regressions. The dependent variable is the monthly DUAL strategy return in Panel A and the monthly TWIN strategy return in Panel B. Independent variables are the contemporaneous monthly strategy returns constructed from alternative inter-firm linkages: text-based industry momentum (TIC RET), geographic links (GEO RET), technological links (TECH RET), conglomerate firms (PC RET), customer momentum (CUS RET), shared analyst coverage (CF RET), and similar stocks (SIM RET). The intercept represents the preserved abnormal returns after controlling for these inter-firm linkages. Other control variables include the six asset pricing factors of Fama and French (2015). Portfolios are value-weighted, and returns are presented in percentages. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses. Because of data constraints, the sample period for columns (1) to (8) starts in July 1989, July 1963, July 1963, July 1977, February 1980, January 1984, July 1963, and July 1989, respectively, and ends in December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dual styles								
Intercept	-0.592	-0.763	-0.762	-0.706	-0.716	-0.545	-0.535	-0.466
	(-2.71)	(-4.02)	(-4.03)	(-2.95)	(-2.58)	(-3.19)	(-3.19)	(-2.76)
TIC RET	-0.795							0.017
	(-8.21)							(0.12)
GEO RET		-0.955						-0.376
		(-8.57)						(-3.75)
TECH RET			-0.568					-0.010
			(-7.82)					(-0.14)
PC RET				-0.526				0.150
				(-7.85)				(2.04)
CUS RET					-0.272			-0.013
					(-3.51)			(-0.29)
CF RET						-0.665		-0.405
						(-11.53)		(-4.80)
SIM RET							-0.697	-0.389
							(-13.76)	(-5.62)
N	384	701	701	534	503	456	701	384
Panel B. Twin styles								
Intercept	0.568	0.878	0.889	0.789	0.793	0.531	0.645	0.444
	(2.47)	(4.92)	(4.76)	(3.38)	(2.82)	(2.51)	(4.09)	(2.38)
TIC RET	0.780							-0.133
	(8.17)							(-1.23)
GEO RET		0.982						0.542
		(7.15)						(4.70)
TECH RET			0.541					0.005
			(5.75)					(0.07)
PC RET				0.528				-0.082
				(5.96)				(-1.24)
CUS RET					0.246			0.010
					(3.22)			(0.20)
CF RET						0.661		0.361
						(9.08)		(4.95)
SIM RET							0.714	0.440
							(13.47)	(6.84)
N	384	701	701	534	503	456	701	384

Table 11. Factor momentum and factor reversals.

This table reports the average monthly returns of three factor-trading strategies. Each factor represents a long-short strategy derived from quintile portfolios (value-weighted), which are constructed by sorting stocks based on a specific characteristic. Each month, factors are sorted into quintiles based on lagged dual-factor return (Panel A), lagged twin-factor return (Panel B), or their own returns in the last month (Panel C). Factor returns are equally weighted within each quintile. A factor-trading strategy longs factors within the top quintile and shorts those within the bottom quintile. For each factor, the set of dual (twin) factors comprises long-short trading strategies sharing negative (positive) correlations in the underlying characteristics with the focal factor. The dual (twin)-factor return is calculated as the absolute correlation-weighted average monthly return of dual (twin) factors. Strategy returns are reported using the raw excess return (Return) and factor-adjusted returns, including the Fama and French (1996) model (FF3), the Carhart (1997) model (Carhart), the Fama and French (2015) model (FF5), the momentum-augmented model (FF6), the momentum and short-term reversal-augmented model (FF6+Rev), the q-factor (Hou et al., 2015) model (Q4), and the expected growth-augmented q-factor (Hou et al., 2021) model (Q5). The sample period is from July 1963 to December 2021. The *t*-statistics with Newey-West adjusted standard errors are shown in parentheses.

	Excess	FF3	Carhart	FF5	FF6	FF6+Rev	Q4	Q5
Panel A. Dual-factor reversal								
Low	0.585	0.642	0.551	0.563	0.492	0.796	0.556	0.423
	(7.05)	(8.29)	(5.40)	(5.90)	(4.92)	(9.65)	(4.67)	(2.87)
High	-0.397	-0.445	-0.457	-0.368	-0.385	-0.648	-0.429	-0.387
	(-4.80)	(-5.70)	(-4.72)	(-4.27)	(-3.98)	(-7.64)	(-4.00)	(-3.06)
High-Low	-0.982	-1.087	-1.007	-0.930	-0.877	-1.444	-0.985	-0.810
	(-6.15)	(-7.30)	(-5.19)	(-5.32)	(-4.57)	(-8.95)	(-4.45)	(-3.00)
Panel B. Twin-factor momentum								
Low	-0.452	-0.515	-0.524	-0.446	-0.460	-0.749	-0.507	-0.426
	(-5.07)	(-6.03)	(-4.95)	(-4.61)	(-4.26)	(-8.57)	(-4.13)	(-2.92)
High	0.562	0.608	0.523	0.555	0.488	0.815	0.556	0.416
	(6.63)	(7.83)	(5.03)	(5.81)	(4.81)	(9.23)	(4.82)	(3.07)
High-Low	1.014	1.123	1.046	1.001	0.948	1.564	1.064	0.842
	(6.08)	(7.24)	(5.14)	(5.42)	(4.67)	(9.40)	(4.58)	(3.06)
Panel C. Own-factor momentum								
Low	-0.532	-0.581	-0.591	-0.505	-0.522	-0.874	-0.581	-0.429
	(-5.89)	(-6.52)	(-5.21)	(-4.83)	(-4.44)	(-9.76)	(-4.31)	(-2.98)
High	0.587	0.653	0.551	0.589	0.509	0.899	0.580	0.414
	(6.76)	(8.17)	(5.06)	(5.74)	(4.60)	(10.48)	(4.39)	(2.76)
High-Low	1.119	1.233	1.142	1.094	1.030	1.773	1.161	0.843
	(6.61)	(7.63)	(5.26)	(5.42)	(4.63)	(10.69)	(4.43)	(2.92)

Appendix to "Style Switching and Asset Pricing"

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

A1. Additional empirical results

Table A1 reports panel regression results of the trading of low-active and high-active institutions on style returns. I use the Brian Bushee *Institutional Investor Classification* to identify low-active and high-active institutions. Specifically, low-active institutions are those classified as "dedicated" or "quasi-indexer", while high-active institutions are those classified as "transient".

Table A2 reports one-sort portfolio results based on alternative predictor specifications, including (1) style returns orthogonal to the short-term reversal effect; (2) dual and twin styles constructed using different δ values; and (3) equal-weighted and absolute cosine similarity-weighted style returns.

Table A3 reports style strategy returns, where dual and twin styles are constructed based on two (Panel A), three (Panel B), or four (Panel C) characteristics.

Table A4 reports the result on placebo tests. It presents one-sort portfolio results based on pseudo style returns, where pseudo styles are constructed based on return correlations among stocks.

A2. Construction of inter-firm linkages

This section describes the details of the construction of inter-firm linkage variables that are omitted in the paper.

1. *Text-based industry momentum (TIC RET).* The 10-K text-based similarity data are downloaded from the Hoberg-Phillips Data Library.[30] The data file contains the firm identifier (gvkey), year, and firm-to-firm similarity scores. The dataset is merged to add the stock identifier (permno) of CRSP using the CCM link table provided by Wharton Research Data Services (WRDS). For each stock, TIC RET is calculated as the similarity score-weighted average monthly return of peer stocks.

2. *Geographic links (GEO RET).* Headquarters location data are obtained from Compustat. I identify each firm's headquarters location based on the ZIP code. The geographic peer

[30] Hoberg-Phillips Data Library, `http://hobergphillips.tuck.dartmouth.edu/`

firms are defined through the first three-digit ZIP codes. Then, GEO RET is calculated as the equal-weighted average monthly returns of all other stocks in the same area.

3. *Technological links (TECH RET).* The patent data are provided by Kogan et al. (2017), and contain the patent-permno match panel, the patent-level data, and the patent-CPC class match information.[31] Each year, I calculate the pairwise technological closeness as the uncentered correlation of the patent distributions between all pairs of firms, where patent distributions are computed using a five-year rolling window. Following Lee et al. (2019), TECH RET is calculated as the technology closeness-weighted return of linked firms, assuming that the patent information becomes publicly available six months after the end of the year in which the patent is announced.

4. *Conglomerate firms (PC RET).* Firms' segment accounting and financial information are obtained from Compustat segment files. A firm is defined as a conglomerate (stand-alone) if it operates in more than one (only one) industry and the aggregate segment sales account for more than 80% of the total sales. I calculate the value-weighted average returns of the stand-alone firms within each of the conglomerate firm's industry segments, where industries are defined using two-digit SIC codes. Then, PC RET is defined as a pseudo-conglomerate portfolio constructed using stand-alone firms from the respective industries, weighted by the conglomerate firm's segment sales. Following Cohen and Lou (2012), I impose at least a six-month lag between firm fiscal year-end and portfolio formation.

5. *Customer momentum (CUS RET).* Following Cohen and Frazzini (2008), the data on customer-supplier relationships are obtained from the Compustat segment files. First, I extract each firm's principal customers and identify publicly listed customer firms using firm names. Second, a six-month gap is imposed to ensure the information is available as of portfolio formation. Finally, CUS RET is calculated as the equal-weighted average monthly returns of principal customers.

6. *Similar stocks (SIM RET).* Each month, stocks are represented using five-dimensional characteristic vectors. Following He et al. (2023), I use share price, log of market value, book-to-market, operating profits, and asset growth, and cross-sectionally standardize characteristics such that each variable has zero mean and unit variance. Similarity is defined based on Euclidean distance among stocks. For each stock, SIM RET is calculated as the value-weighted average return of its 50 nearest stocks.

[31] `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`

Table A1. Trading of low-active and high-active institutional investors.
This table reports panel regressions of institutional investors' trading on dual- and twin-style returns, where institutions are classified based on the *Institutional Investor Classification* of Brian Bushee:

$$\Delta Inst_{i,t+1}^{class} = a + b_{style}Style_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}.$$

The classification includes dedicated, quasi-indexer, and transient. In particular, institutions classified as "dedicated" or "quasi-indexer" are considered low-active, while institutions classified as "transient" are considered high-active. The dependent variable (multiplied by 100) is the quarterly change in institutional ownership. DUAL (TWIN) is the lagged cumulative return of dual (twin) style stocks in the past three months. Control variables include the log of market capitalization, the log of the book-to-market ratio, the focal stock's past 3-month return and past 11-month return (skipping the most recent month), asset growth, operating profits, and return volatility. All variables are winsorized at 1% and 99% each quarter. Independent variables are cross-sectionally standardized to have zero mean and unit variance. Regressions feature quarter and industry fixed effects. The t-statistics based on standard errors clustered at quarter and firm levels are reported in parentheses. The sample period is from June 1980 to December 2021.

	Dedicated				Quasi-indexer				Transient			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DUAL	0.007	0.007			-0.014	-0.013			-0.056	-0.054		
	(1.58)	(1.64)			(-0.79)	(-0.70)			(-3.28)	(-3.21)		
TWIN			0.002	0.001			0.028	0.027			0.046	0.045
			(0.45)	(0.28)			(1.63)	(1.52)			(2.96)	(2.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	383095	383386	383095	383386	441107	441476	441107	441476	426807	427143	426807	427143
Adj. R^2	0.01	0.01	0.01	0.01	0.07	0.07	0.07	0.07	0.13	0.14	0.12	0.14

Table A2. Residual styles, parameter choices, and weighting of style returns. This table reports portfolio returns based on DUAL and TWIN. For each stock, DUAL (TWIN) is the weighted monthly return of other stocks sharing negative (positive) cosine similarities within the characteristic space. In each panel, the first row reports portfolios sorted on residual style returns. Residual style returns are calculated as the residual from cross-sectional regressions of DUAL/TWIN on the focal stock's own monthly return. The following three rows report results across various cutoff values (δ) utilized in identifying dual and twin styles; in the last two columns, δ is set at 0.25, while style returns are calculated based on equal-weighted (EW) or absolute cosine similarity-weighted (CW) average returns of stocks within the dual/twin style. Portfolios are value-weighted in Panel A and equal-weighted in Panel B. In all specifications, firm pairs with the same four-digit SIC industry classifications are excluded. Each month, stocks are sorted into quintile portfolios based on DUAL or TWIN. The table presents the monthly returns of the top and bottom quintile portfolios, as well as the returns of the high-minus-low hedge strategy. The sample period is from July 1963 to December 2021. The t-statistics with Newey-West adjusted standard errors are shown in parentheses.

	DUAL			TWIN		
	Low	High	High-Low	Low	High	High-Low
Panel A. Value-weighted portfolios						
Residual	1.236	0.197	-1.038	0.132	1.182	1.050
	(4.85)	(0.97)	(-5.19)	(0.54)	(4.35)	(5.34)
$\delta = 0.15$	1.197	0.272	-0.925	0.196	1.159	0.964
	(4.77)	(1.33)	(-4.50)	(0.77)	(4.28)	(4.57)
$\delta = 0.20$	1.234	0.265	-0.969	0.171	1.174	1.003
	(4.86)	(1.29)	(-4.61)	(0.68)	(4.36)	(4.74)
$\delta = 0.30$	1.215	0.297	-0.918	0.152	1.200	1.049
	(4.67)	(1.41)	(-4.34)	(0.61)	(4.59)	(5.18)
EW	1.152	0.201	-0.951	0.242	1.137	0.895
	(4.77)	(0.84)	(-4.64)	(0.98)	(4.74)	(4.67)
CW	1.148	0.235	-0.913	0.163	1.152	0.989
	(4.74)	(0.98)	(-4.40)	(0.66)	(4.67)	(4.94)
Panel B. Equal-weighted portfolios						
Residual	1.653	0.144	-1.509	0.207	1.504	1.297
	(5.85)	(0.64)	(-8.10)	(0.80)	(4.79)	(7.46)
$\delta = 0.15$	1.500	0.305	-1.195	0.328	1.391	1.063
	(5.38)	(1.39)	(-6.10)	(1.24)	(4.38)	(5.74)
$\delta = 0.20$	1.510	0.298	-1.211	0.316	1.405	1.088
	(5.39)	(1.36)	(-6.19)	(1.20)	(4.41)	(5.88)
$\delta = 0.30$	1.519	0.298	-1.221	0.275	1.423	1.147
	(5.29)	(1.33)	(-6.13)	(1.06)	(4.52)	(6.24)
EW	1.466	0.223	-1.243	0.257	1.523	1.266
	(5.27)	(0.88)	(-6.57)	(0.98)	(5.31)	(6.96)
CW	1.457	0.262	-1.195	0.209	1.548	1.339
	(5.19)	(1.02)	(-6.28)	(0.80)	(5.40)	(7.20)

Table A3. Dual and twin styles from alternative characteristic combinations. This table reports the average returns of strategies based on DUAL and TWIN. The set of characteristics used to construct styles includes the book-to-market ratio (BM), operating profits (OP), asset growth (AG), momentum (MOM), and volatility (VOL). In Panel A and Panel B, the upper and lower triangular sections respectively display strategy returns based on DUAL and TWIN. In Panel A, styles are formed using characteristic pairs. For instance, the cell (AG, OP) shows the average TWIN strategy return, with twin styles identified using asset growth and operating profits; the cell (OP, MOM) indicates the average DUAL strategy return, where dual styles are determined using operating profits and momentum. In Panel B, styles are constructed using three characteristics. For example, cell (AG, OP) displays the average TWIN strategy return, with twin styles constructed based on characteristics excluding asset growth and operating profits. In Panel C, styles are formed using four characteristics, with each column displaying results from styles excluding the corresponding characteristic. For instance, column BM represents the average strategy returns of DUAL and TWIN, where dual and twin styles are formed excluding the book-to-market ratio. Portfolios are value-weighted. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses. The sample period is from July 1963 to December 2021.

Panel A. Styles from characteristic pairs

TWIN\DUAL	BM	OP	AG	MOM	VOL
BM	-	-0.398	-0.571	-0.433	-0.929
		(-3.19)	(-4.15)	(-3.10)	(-4.51)
OP	0.200	-	-0.606	-0.578	-0.915
	(1.73)		(-4.35)	(-4.04)	(-4.50)
AG	0.326	0.483	-	-0.484	-0.870
	(2.84)	(3.30)		(-3.71)	(-4.50)
MOM	0.501	0.306	0.308	-	-0.967
	(3.82)	(2.45)	(2.42)		(-4.57)
VOL	0.859	0.529	0.599	0.909	-
	(3.96)	(3.17)	(3.68)	(4.47)	

Panel B. Styles excluding characteristic pairs

TWIN\DUAL	BM	OP	AG	MOM	VOL
BM	-	-0.958	-0.950	-0.998	-0.565
		(-4.52)	(-4.46)	(-5.05)	(-3.71)
OP	0.919	-	-0.950	-0.978	-0.494
	(4.43)		(-4.40)	(-4.75)	(-3.58)
AG	0.962	0.981	-	-0.923	-0.439
	(4.56)	(4.68)		(-4.42)	(-3.15)
MOM	0.617	0.908	0.863	-	-0.524
	(3.63)	(4.25)	(3.98)		(-4.02)
VOL	0.406	0.537	0.467	0.351	-
	(3.02)	(3.90)	(3.52)	(3.04)	

Panel C. Styles excluding one characteristic

	BM	OP	AG	MOM	VOL
DUAL	-0.959	-0.965	-0.998	-0.985	-0.504
	(-4.46)	(-4.44)	(-4.61)	(-4.82)	(-3.67)
TWIN	0.974	1.012	0.995	0.959	0.530
	(4.62)	(4.85)	(4.81)	(4.49)	(3.91)

Table A4. One-sort portfolios based on pseudo dual- and twin-style returns. This table reports portfolio returns based on pseudo dual- and twin-style returns. For each stock, the pseudo dual style and the pseudo twin style are identified based on its correlations in daily model-adjusted returns with other stocks (ρ^{model}) within a month. Three different return metrics are considered when computing correlations: (1) the raw excess return (ρ^{RF}), which is the daily stock return minus the daily risk-free rate; (2) the market-adjusted return (ρ^{CAPM}), which is the residual from firm-by-firm regressions of daily excess return against daily market excess return; and (3) the five-factor-adjusted return (ρ^{FF5}), which is the residual from firm-by-firm regressions of daily excess return against daily Fama and French (2015) five-factor returns. Pseudo DUAL (TWIN) is calculated as the value-weighted average monthly return of stocks within the pseudo dual (twin) style. In Panel A, stocks are sorted into quintile portfolios based on Pseudo DUAL and Pseudo TWIN, respectively. In Panel B, I conduct monthly cross-sectional regressions of Pseudo DUAL/Pseudo TWIN on the focal stock's contemporaneous monthly return and take the residuals. Then, stocks are sorted into quintile portfolios based on these residual pseudo-style returns. Portfolios are value-weighted and held for one month. The sample period is from July 1963 to December 2021. The t-statistics with Newey-West adjusted standard errors are shown in parentheses.

	ρ^{RF}		ρ^{CAPM}		ρ^{FF5}	
	Pseudo DUAL	Pseudo TWIN	Pseudo DUAL	Pseudo TWIN	Pseudo DUAL	Pseudo TWIN
Panel A. Raw pseudo-style returns						
Low	0.629	0.570	0.636	0.615	0.681	0.538
	(3.46)	(3.01)	(3.40)	(3.17)	(3.82)	(2.88)
2	0.603	0.615	0.580	0.532	0.472	0.619
	(3.35)	(3.33)	(3.24)	(2.85)	(2.70)	(3.42)
3	0.616	0.658	0.600	0.616	0.647	0.615
	(3.18)	(3.73)	(3.25)	(3.48)	(3.70)	(3.41)
4	0.632	0.620	0.564	0.635	0.585	0.562
	(3.46)	(3.40)	(3.05)	(3.59)	(3.14)	(3.17)
High	0.506	0.570	0.537	0.552	0.592	0.612
	(2.81)	(2.90)	(2.91)	(2.94)	(3.12)	(3.49)
High-Low	-0.123	0.000	-0.099	-0.063	-0.089	0.074
	(-1.31)	(0.00)	(-0.91)	(-0.51)	(-1.19)	(0.89)
Panel B. Pseudo style returns orthogonal to short-term reversal						
Low	0.626	0.522	0.630	0.607	0.684	0.541
	(3.45)	(2.79)	(3.39)	(3.13)	(3.88)	(2.90)
2	0.622	0.618	0.582	0.531	0.478	0.618
	(3.40)	(3.41)	(3.26)	(2.86)	(2.70)	(3.39)
3	0.624	0.644	0.611	0.609	0.656	0.615
	(3.22)	(3.58)	(3.29)	(3.39)	(3.75)	(3.44)
4	0.615	0.617	0.555	0.648	0.574	0.565
	(3.31)	(3.44)	(3.00)	(3.73)	(3.08)	(3.20)
High	0.514	0.582	0.547	0.553	0.583	0.617
	(2.93)	(3.00)	(2.97)	(2.95)	(3.06)	(3.51)
High-Low	-0.112	0.061	-0.084	-0.054	-0.101	0.076
	(-1.21)	(0.46)	(-0.79)	(-0.44)	(-1.34)	(0.93)