Demand Shifts and Asset Pricing *

Huaixin Wang

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Abstract

This paper studies asset prices in a market with active investment. As investors employ characteristics-managed portfolios, assets share exposure to demand shocks from rebalancing. The propagation of shocks leads to cross-asset reversal (momentum) among assets with negatively (positively) correlated characteristics. Trading strategies that empirically exploit this price impact yield annualized returns of 12%. Active rather than passive institutions' trading drives the result, with the return predictability amplified during periods of heightened institutional attention. These findings suggest a destabilization effect of quantitative trading and provide a potential explanation for predictable return patterns of characteristic-sorted portfolios.

JEL Classification: G11, G12, G14, G23

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1 Introduction

Characteristics-based investing is pervasive in asset management, and active investors typically designate quantitative trading strategies based on a complex set of attributes.[1] While this approach offers benefits to the asset management industry, shifts in demand for stock characteristics might in turn distort prices (Gompers and Metrick, 2001; Barberis and Shleifer, 2003; Khandani and Lo, 2011; Edelen et al., 2016; DeVault et al., 2019). A recent study by Davis (2025) documents the prevalent inelastic demand of quantitative strategies, implying that these capital reallocations could exert large price impacts.

This paper proposes a characterization of active investment and its asset pricing implications. I show that rebalancing characteristics-managed portfolios induces propagation of demand shocks. Assets with varying characteristics share correlated exposures, leading to cross-correlation in returns. The framework provides an empirically testable structure of price contagion, allowing me to assess the market impact of characteristics-driven investing in a nuanced way.

To formalize my intuition, I consider a stylized model building on Barberis and Shleifer (2003) and Greenwood (2005), with two specifications: (1) *Characteristics-managed portfolio* (Brandt et al., 2009): investors designate trading strategies based on firm attributes such as valuation, investment, and profitability. The loading of asset demand on each characteristic, as determined by portfolio optimization, captures the active decision weight along that dimension in capital allocation; (2) *Short-term extrapolative belief* (Greenwood and Shleifer, 2014; Bastianello and Peng, 2025): expectations about near-term asset payoffs depend positively on recent realized returns. This simple framework enables stock-level tests to examine the underlying mechanism, while also speaking to patterns observed in characteristics-sorted portfolios, such as short-term momentum (Lewellen, 2002; Ehsani and Linnainmaa, 2022; Arnott et al., 2023) and long-run reversal (Favero et al., 2023; Li and Yan, 2024).

The intuition is as follows. When investors engage in characteristics-based trading, the propensity for investing in a specific characteristic depends on the expected return associated with that dimension. Consequently, asset demand can be described by a combination of characteristic-sorted portfolios.[2] In particular, an asset's characteristic values represent its

[1]For instance, in a survey conducted by Invesco (2023) of 130 investors managing $22.5 trillion in assets, over 90% of respondents cite "Factor-based investing" in their portfolio construction methodologies; nearly three-quarters of investors report frequently adjusting factor weights based on expected performance and the need to balance portfolio exposures. Figure 1 depicts the proportions of hedge funds categorized by strategy. As of December 2023, around 36% of U.S. hedge funds (excluding fund of funds) in the Lipper-TASS database are classified as the Long/Short Equity Hedge strategy.

[2]As a benchmark comparison, recall that in the conventional Capital Asset Pricing Model (CAPM), investors hold a combination of the market portfolio and the risk-free asset.

exposure to demand shocks along various dimensions. Therefore, between assets with opposite (aligned) characteristic exposures, demand shocks exert negative (positive) spillover effects. Short-term extrapolative beliefs imply that the investor is inclined to ride price trends over the near term. As a result, the demand for any asset i tends to decrease (increase) in response to the recent returns of assets sharing negative (positive) correlations in characteristics. In other words, asset demand exhibits *shifts*, the direction of which is determined by the competitive relationships among assets within the characteristic space.

For expositional convenience, I refer to assets with negative characteristic correlations as *dual* and those with positive correlations as *twin*. The model predicts that dual assets exhibit cross-reversals, whereas twin assets typically display cross-momentum. As these patterns arise from price impacts induced by characteristics-based trading, the predictability eventually dissipates over the long run.

In my empirical tests, I identify dual and twin assets by calculating cosine similarities between stocks along several dimensions, including value, profitability, investment, volatility, and momentum. I then define the DUAL (TWIN) signal as the value-weighted average monthly return of stocks sharing negative (positive) cosine similarities with the focal stock. Consistent with the demand-shifting story, DUAL negatively predicts cross-sectional returns, whereas TWIN is positively associated with future returns. Specifically, 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. The findings remain robust after adjusting for conventional asset pricing factors and controlling for confounding variables in Fama and MacBeth (1973) regressions.

The documented predictability reflects the price impact of characteristics-driven demand shifts. Specifically, the focal stock's price deviates downward from the fundamental value as the effective demand switches to dual stocks, whereas the stock tends to be overpriced as investors chase twin stocks' performance. Therefore, the profits of DUAL and TWIN strategies should eventually reverse in the long run. Indeed, the magnitude of returns for the two 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 demand shifts from alternative explanations such as information diffusion (Cohen and Frazzini, 2008) or time-varying risk premium, under which the returns should be persistent rather than transient. In addition, the strategy returns 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 is the

shifting of demand between dual and twin stocks. I conduct a series of tests to validate this channel. First, I examine variations in institutional demand (Edelen et al., 2016; McLean et al., 2020) by regressing quarterly changes in institutional ownership on recent dual- and twin-stock returns. I find that an increase in dual (twin) returns implies a decrease (an increase) in institutional demand for the focal stock. This result supports the hypothesis that investors are inclined to withdraw funds and rotate into other stocks in the presence of high dual returns, whereas they continue to purchase the focal stock when twin stocks performed well. Further analysis suggests that highly active institutions serve as the primary marginal investors, with their demand shifts driving the pricing effect. As a comparison, less active institutions exhibit minimal demand shifts. 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.

Second, I examine the role of institutional attention. Using Bloomberg readership as a measure of institutional investor attention (Ben-Rephael et al., 2017), I show that the returns of DUAL and TWIN strategies are realized entirely following periods with high institutional attention. In contrast, retail investor attention (Da et al., 2011) or market sentiment (Baker and Wurgler, 2006) do not exhibit any predictive ability for these effects. This result complements the evidence on institutional trading and highlights the role of professional traders' demand shifts in affecting asset prices.

Third, I show that the return magnitude of dual stocks negatively correlates with subsequent institutional attention in the cross-section. This finding suggests that characteristics-based competing assets induce distractions and redirect attention away from the focal stock. Therefore, the pricing results documented in this paper are more likely to be driven by active investment decisions rather than automatic rebalancing or passive investing.

I conduct several additional tests to further validate the robustness of my findings. Consistent with institutions being primary short sellers (Boehmer et al., 2008), I show that subsequent changes in the short interest ratio are significantly higher (lower) for stocks with high DUAL (TWIN) compared to those with low DUAL (TWIN). Variations in short interests are evident within a one-year period, followed by a deceleration in trading activity over the long term. This trading pattern aligns with the diminishing long-term performance of cross-predictability strategies. In contrast, retail investors tend to act as followers rather than marginal traders, as they retain purchases over longer horizons. My main findings are also robust to controlling for other lead-lag effects in spanning regressions, purging out the short-term reversal effect, different parameter choices, and alternative combinations of characteristics used in constructing signals. I further conduct a placebo test by defining dual and twin stocks based on return correlations rather than characteristic correlations. The

resulting signals do not exhibit predictive power for future returns.

Related literature. This paper contributes 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 benchmarking (Basak and Pavlova, 2013; Baltussen et al., 2019; Buffa and Hodor, 2023; Pavlova and Sikorskaya, 2023).[3] This paper contributes to the literature by delving into the impacts of characteristics-based quantitative trading, a well-established and widely utilized strategy within the financial industry. While prior research has primarily focused on correlated demand shocks from passive investment, I highlight the role of active asset management. My findings also align with Brunnermeier and Nagel (2004), Griffin et al. (2011), and Edelen et al. (2016) that institutional investors' demand could amplify mispricing.

An extensive literature studies inelastic demand and the market impact of style investing, starting with the seminal work by Barberis and Shleifer (2003) and Greenwood (2005).[4] Prior research examines the asset pricing implications of style investing through market indices (Barberis et al., 2005; Greenwood, 2008; Boyer, 2011) and stock categorization (Green and Hwang, 2009; Wahal and Yavuz, 2013; Hameed and Xie, 2019; Kacperczyk et al., 2023). My paper contributes to this literature in several ways. First, I show that the traditional style investing behavior can be nested within a broader framework of characteristics-based demand. Second, I introduce a generalized approach to analyzing asset interdependencies in a high-dimensional setting, whereas existing studies predominantly focus on one category at a time. Third, I document both cross-reversal and cross-momentum, whereas prior studies have concentrated on contemporaneous comovement or momentum in isolation. Finally, my results suggest that highly active institutions play a crucial role in driving the observed pricing pattern, whereas previous research focuses on market indices and passive investors. This distinction also sets this paper apart from existing work.

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

[3]In addition, institutional trading and arbitrage activity also affects anomaly returns such as value and momentum (Chen et al., 2022; Lou and Polk, 2022; Ben-David et al., 2023; Peng and Wang, 2023). 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 impact of demand shocks on asset prices. See also Gabaix and Koijen (2021) for a recent review.

[4]Several follow-up studies examine 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).

corresponding cross-stock momentum effects, with two primary explanations. 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).[5] The other branch proposes that continued overreaction-driven demand by retail investors also contributes to cross-predictability (e.g., Chen et al. (2023)). Distinct from these studies, demand shifting highlights the *coexistence* of cross-reversals and cross-momentum, while also emphasizing the crucial role of institutional investors. Moreover, the pricing effect of dual and twin stocks remains robust even after controlling for other inter-firm linkages.

Finally, this paper 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 institutions' demand for characteristics as a potential explanation for the predictability pattern in factor returns.[6] However, it is worth noting that the evidence thus far is silent on the causal role of demand shifts in generating factor momentum. A more rigorous examination would require granular transaction-level data or exogenous shocks to institutional appetite for characteristics, which are beyond the scope of this paper.[7] Nevertheless, the stock-level evidence serves as a supplement to existing literature and sheds light on possibilities for future research in this area.

The rest of the paper is structured as follows. Section 2 provides a conceptual framework. Section 3 describes the empirical construction of dual and twin stocks. Section 4 presents the main empirical results on the asset pricing implications of demand shifts. Section 5 examines institutional investors' trading and attention. Section 6 provides additional robustness tests. I conclude in Section 7.

2 Conceptual framework

In this section, I formalize the intuition in a simple model building on Barberis and Shleifer (2003) and Greenwood (2005). Rather than directly assuming switches of capital between two categories (as in Barberis and Shleifer (2003)), I derive investor demand in a general

[5]These inter-firm links include, 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).

[6]Gompers and Metrick (2001) suggest that common demand shocks from the institutional appetite for various stock characteristics may induce correlation in returns. Aligning with their perspective, I show that demand shifting serves as a plausible mechanism for generating interdependence in returns across assets and portfolios. As such, demand shifting also provides a potential explanation for the findings of Lewellen (2002), who demonstrate that excess covariance among stocks contributes to serial correlation in portfolio returns.

[7]For example, Ben-David et al. (2022, 2023) find that a June 2002 reform in Morningstar's mutual fund rating methodology generates substantial impacts on style-level demand and profitability of factors.

setting with characteristics-managed portfolios. In this framework, shifts in asset demand emerge naturally from portfolio optimization. I also draw inspiration from Greenwood (2005) that shocks spillover among assets according to their roles in arbitrage positions. Importantly, the model accommodates rich asset characteristics and provides guidance for empirical implementation.

I streamline the analysis by focusing on a simple portfolio choice problem to highlight the empirical implications. Appendix A1 provides a characterization of equilibrium prices.

2.1 Assets and portfolio choice

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 $\mathbf{V}$, 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 in period t.

A *quant trader* in this economy chooses a portfolio $\mathbf{N}^q_t = (N^q_{1,t}, \ldots, N^q_{N,t})'$ to maximize mean-variance utility, taking fundamental risk into account. The term $N^q_{i,t}$ is the amount of capital allocated to asset i. The optimal portfolio choice problem is given by

$$\max_{\mathbf{N}^q_t} \mathbb{E}^q_t(\mathbf{P}_{t+1} - \mathbf{P}_t)'\mathbf{N}^q_t - \frac{\gamma_q}{2}(\mathbf{N}^q_t)'\mathbf{V}\mathbf{N}^q_t, \tag{2}$$

where γ_q 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 by employing characteristics-managed portfolios.

Assumption 2.1. ***Characteristics-managed portfolio.*** *The trading strategy adopted by the quant trader is an affine function of K firm characteristics:*

$$\mathbf{N}^q_t = \Theta\mathbf{\Omega}_t, \tag{3}$$

where $\Theta = (C_1, ..., C_N)'$ *is an* $N \times K$ *matrix of asset characteristics (e.g., book-to-market) and each row* $C_i' = (c_i^1, ..., c_i^K)$ *is the vector of characteristics of asset* i*;* $\mathbf{\Omega}_t = (\omega_{1,t}, ..., \omega_{K,t})'$ *is a* K*-vector of strategy loading on characteristics. Equivalently, for each asset* i*, the quant demand is a linear combination of the asset's characteristics, weighted by the portfolio's loading:* $N_{i,t}^q = C_i \mathbf{\Omega}_t = c_i^1 \omega_{1,t} + c_i^2 \omega_{2,t} + \cdots + c_i^K \omega_{K,t}$.

A crucial property of $\mathbf{\Omega}_t$ is that $\omega_{k,t}$ remains constant across assets for each attribute k. This captures the core of characteristics-driven investing in the sense that the investor prioritizes characteristics over specific stocks. Therefore, variation in characteristics is the primary source of the variation in demand. The demand loading on a characteristic, $\omega_{k,t}$, captures the active decision weight for this specific attribute. For example, let BM denote the book-to-market ratio. Then, $\omega_{BM,t} > 0$ indicates a value strategy, as the investor tends to buy stocks with high book-to-market ratios.[8]

The investor actively trades on characteristics, with $\mathbf{\Omega}_t$ being determined endogenously through portfolio optimization. This process differentiates demand shifts from passive index investing, where $\mathbf{\Omega}_t$ is primarily determined by exogenous factors such as investment mandates, and constrained by tracking error requirements. I compare the demand-shifting patterns across different types of institutions in subsequent empirical analysis. Consistent with this interpretation, the results indicate that institutions with a higher degree of active management and less benchmarking constraints exhibit more pronounced demand shifts.

Assumption 2.2. ***Short-term return extrapolation.*** *The quant trader forms expectations of next-period returns by extrapolating recent price changes:*

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

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

Extrapolative belief has been shown to be an important driving force underlying many financial market anomalies. Greenwood and Shleifer (2014) show that extrapolation 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

[8] In this paper, I refrain from distinguishing between different mechanisms behind characteristics-based trading. Given the focus on the asset pricing implications of demand shifts, 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.

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). 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.[9]

While the origins and evidence of extrapolative beliefs remain debatable, recent research by Bastianello and Peng (2025) demonstrates that market participants consistently exhibit extrapolative expectations over *short horizons*. Assumption 2.2 can be interpreted as professional traders riding market mispricing without immediately correcting it (Brunnermeier and Nagel, 2004; Griffin et al., 2011). Aligned with this view, empirical analysis in Section 5.1 reveals that highly active institutions with elevated portfolio turnover are the primary drivers of demand shifts, as they prioritize short-term returns over long-term investment objectives. A distinction also emerges between professional traders and unsophisticated investors. Results in Section 6.1 suggest that short sellers engage in shifting-based trading over the short term, whereas retail investors merely follow price trends and persistently trade even over the long term.

2.2 Derivation of asset demand

The first-order condition of problem (2) gives the optimal strategy:

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

That is, the propensity for investing in a specific characteristic depends on the expected payoff along that dimension (i.e., $\sum_{i=1}^{N} c_i^k \mathbb{E}_t^q(P_{i,t+1} - P_{i,t})$).[10] Consequently, the demand function is given by

$$\mathbf{N}_t^q = \frac{1}{\gamma_q}\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'\mathbb{E}_t^q[\mathbf{P}_{t+1} - \mathbf{P}_t]. \tag{5}$$

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

[9] 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 renders the analysis more tractable when prices are determined in equilibrium. Nevertheless, demand shifts are unaffected by assuming away this one-period lag in belief formation. The key aspect of asset demand in my model lies in the assumption that the manager adopts a characteristics-based trading strategy. Extrapolative belief without lags is also employed in related studies such as Barberis et al. (2015) and Pan et al. (2021).

[10] 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.

the demand for any risky asset i can be written as

$$N_{i,t}^{q} = \frac{1}{\gamma_q} \sum_{j=1}^{N} C_i'(\Theta'\mathbf{V}\Theta)^{-1} C_j \mathbb{E}_t^q(P_{j,t+1} - P_{j,t}). \tag{6}$$

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

$$\begin{aligned} N_{i,t}^{q} = & \underbrace{\frac{1}{\gamma_q} \sum_{\{p | C_i'(\Theta'\mathbf{V}\Theta)^{-1}C_p < 0\}} C_i'(\Theta'\mathbf{V}\Theta)^{-1} C_p \mathbb{E}_t^q(P_{p,t+1} - P_{p,t})}_{\textit{Dual assets}} \\ & + \underbrace{\frac{1}{\gamma_q} \sum_{\{q | C_i'(\Theta'\mathbf{V}\Theta)^{-1}C_q > 0\}} C_i'(\Theta'\mathbf{V}\Theta)^{-1} C_q \mathbb{E}_t^q(P_{q,t+1} - P_{q,t})}_{\textit{Twin assets}} \end{aligned} \tag{7}$$

A simple case to illustrate the demand function is to consider a single characteristic with coarse values. Suppose the investor's trading strategy is based on the book-to-market ratio. By sorting assets into buckets according to their book-to-market ratio, we can define a one-dimensional characteristic c_i, where $c_i = 1$ if stock i is classified as *Value* and $c_i = -1$ if stock i is classified as *Growth*. Let i be a value stock, then equation (7) reduces to

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

That is, the investor's time t allocation to stock i depends on the value category's recent performance relative to that of the growth category. This structure nests the specification of Barberis and Shleifer (2003) within a general yet parsimonious framework. Empirical evidence from several studies (e.g., Calluzzo et al. (2019), Chen et al. (2019), and Broman and Moneta (2024)) demonstrates that institutional investors, particularly hedge funds and high-turnover institutions, actively engage in trading based on firm characteristics. I extend beyond this observation to examine the price impact resulting from the widespread implementation of these strategies on the interdependence of asset returns.

2.3 Demand shifts and pricing implication

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

$$N_{i,t}^{q} \propto \frac{1-\theta}{\gamma_q} \sum_{j=1}^{N} \left[C_i'(\Theta' \mathbf{V} \Theta)^{-1} C_j \left(\sum_{l=1}^{t-1} \theta^{l-1} (P_{j,t-l} - P_{j,t-l-1}) \right) \right]. \tag{9}$$

The demand response of the focal asset to the recent performance of other assets is thus governed by the joint distribution of characteristics. In particular, we have the following proposition:

Proposition 1. ***Demand shifts.*** *For any risky asset i, the investor's demand for asset i decreases (increases) in response to the recent returns of dual (twin) assets.*[11]

This proposition suggests that the quant trader tends to withdraw capital from the focal asset and shift towards dual assets when the latter appear attractive. Conversely, the investor augments the position in the focal stock when twin assets show strong performance. Empirically, shifts in demand are more likely to be observed among active investors employing quantitative trading strategies. In this way, the adoption of characteristics-managed portfolios propagates demand shocks across assets, thereby generating price impact. This mechanism thus delivers the following asset pricing implications:

Corollary 1. ***Short-term cross-correlations.*** *The returns of risky assets tend to decrease (increase) with respect to the recent returns of dual (twin) assets.*

Corollary 2. ***Long-term reversals.*** *The cross-asset return predictability tends to diminish and eventually reverse over longer horizons.*

To establish these corollaries, Appendix A1 presents a simple extended model by introducing a fundamental investor targeting conventional mean-variance portfolios. As a consequence of asset-level predictability, the return dynamics of characteristic-sorted portfolios can be expressed as

$$\Theta' \mathbf{R}_t \propto \varepsilon_t + \frac{\gamma_f}{\gamma_q} (1-\theta) \Theta' \left[\mathbf{R}_{t-1} - (1-\theta) \sum_{l=1}^{t-2} \theta^{l-1} \mathbf{R}_{t-l-1} \right], \tag{10}$$

where $\mathbf{R}_t = \mathbf{P}_t - \mathbf{R}_{t-1}$ and γ_f is the risk aversion parameter of the fundamental investor. Therefore, the framework also provides a potential explanation for the short-term momentum

[11] Note that $\partial N_{i,t}^{q} / \partial (P_{j,t-l} - P_{j,t-l-1}) = (1-\theta)\theta^{l-1} C_i'(\Theta' \mathbf{V} \Theta)^{-1} C_j$. Given that $(1-\theta)\theta^{l-1} > 0$, the proposition follows directly from the definition of dual and twin assets.

in characteristic-sorted portfolios (Lewellen, 2002; Ehsani and Linnainmaa, 2022; Arnott et al., 2023) and their long-term reversals (Favero et al., 2023; Li and Yan, 2024).

The subsequent analysis concentrates on the empirical implementation 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.

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 market 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 Definition of dual and twin stocks

The initial step of identifying dual and twin stocks is the definition of the characteristic space. I consider five prevailing dimensions, including value, profitability, investment, volatility, and momentum.[12] 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

[12]In my main analysis, size (i.e., log of market capitalization) is not included 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 for demand shifts, which involve highly active strategies. Second, the size distribution exhibits extreme skewness, making results sensitive to how market value is adjusted. Nevertheless, the pricing effect of dual and twin stocks remains valid when size is integrated into the identification process. In robustness tests, I indeed find that highly active institutions display demand shifts as opposed to passive ones.

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 dimensions for several reasons. First, value, profitability, and 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) also suggests that these dimensions are important in explaining the covariance structure of stock returns. In the robustness section, I shall show that each characteristic contributes to the 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 stocks. 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 assets 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:

$$COS_{i,j} = \frac{C_i \cdot C_j}{\|C_i\|\|C_j\|}, \tag{11}$$

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 stock i, the dual ($\mathcal{D}$) and twin ($\mathcal{T}$) stocks are defined as follows:

$$\mathcal{D}(i) = \{j | j \neq i,\ COS_{i,j} < -\delta\}, \quad \mathcal{T}(i) = \{j | j \neq i,\ COS_{i,j} > \delta\}, \tag{12}$$

in which $\delta \in [0, 1)$ governs the precision and inclusiveness in classification. Figure 2 provides a visual representation of dual and twin assets within a two-dimensional characteristic space. A larger δ yields a stricter classification, leading to narrower sets. Conversely, a smaller δ widens the scope of dual and twin assets but at the expense of precision. In the main analysis, I choose a moderate cutoff by setting δ 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 stocks are identified on an annual basis. At the end of June of each year t, I calculate cosine similarities among stocks based on equation (11). For each stock, the sets of dual and twin stocks are determined by equation (12). 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) class:[13]

$$\text{DUAL}_{i,t} = \frac{1}{\sum_{j\in\mathcal{D}(i)} w_{j,t}} \sum_{j\in\mathcal{D}(i)} w_{j,t} R_{j,t}, \quad \text{TWIN}_{i,t} = \frac{1}{\sum_{j\in\mathcal{T}(i)} w_{j,t}} \sum_{j\in\mathcal{T}(i)} w_{j,t} R_{j,t}, \tag{13}$$

where $R_{j,t}$ denotes the monthly return of stock j and $w_{j,t}$ is its market value. Note that dual and twin are *relative* concepts defined for each focal stock. Cross-reversal (cross-momentum) refers to the prediction that DUAL (TWIN) is negatively (positively) associated with expected stock returns.

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. Panel A of Table 1 shows that the focal stock's contemporaneous monthly return is lower when the dual-stock return is high. This aligns with demand shifts causing price distortions: if two stocks have negatively correlated characteristics, their price comovement should be lower than what their fundamental correlation alone would predict.

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. Overall, firm characteristics are distributed nearly symmetrically across DUAL and TWIN quintiles, and no clear monotonic patterns emerge.

[13] I winsorize market capitalization at the 1% and 99% levels cross-sectionally when computing DUAL and TWIN to prevent a few very large firms from dominating the signals. I also consider alternative weighting schemes in robustness tests. My main findings are insensitive to this specification.

4 Asset pricing results

This section presents empirical evidence on the asset pricing implications of demand shifts. I first conduct one-sort portfolios based on dual- and twin-stock returns to examine the key 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 confounding factors. I also study the role of macroeconomic conditions and the long-horizon returns of strategies to tease out the potential channels. Lastly, I conduct spanning tests using cross-stock return predictability anomalies from economic links.

4.1 Cross-correlations from demand shifts

This section examines the main prediction regarding serial correlations in returns. 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 stocks exhibit cross-reversal, whereas twin stocks exhibit cross-momentum. Specifically, high-DUAL stocks *underperform* low-DUAL stocks by 1.00% per month (t-stat=-4.60). That is, when a stock's dual peers performed well recently, that stock tends to yield lower returns because of capital shifting away from it. The return of the DUAL 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 likely arises from the negative comovement between DUAL and the focal stock's contemporaneous return. The performance of the dual-stock strategy is enhanced by controlling for the short-term reversal effect, which is mainly driven by factors other than demand shifts, such as illiquidity (Avramov et al., 2006; Nagel, 2012; Dai et al., 2024).

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 stocks is not unique to this paper, as previous studies such as Lewellen (2002), Chen (2003), Wahal and Yavuz (2013), and Chou et al. (2019) have also shown that past returns of firms with similar characteristics positively predict cross-sectional expected returns. Hence, twin-stock momentum on its own is not a new phenomenon nor definitive proof of demand shifts. The novel finding of this paper is the negative lead-lag returns relation among dual stocks. The mechanism behind twin-stock momentum could include other forces, whereas the cross-stock reversals among dual stocks are more directly tied to the demand-shifting story.

One concern regarding the return predictability result is that DUAL and TWIN are potentially correlated. By construction, dual and twin stocks exhibit opposite directions in their underlying characteristics, 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 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.[14] 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-reversal in dual stocks is unlikely to be driven solely by the correlation between the two proposed signals. In fact, it appears that the demand-shift mechanism is a key driver behind the twin-stock momentum as well, rather than alternative channels. In later analysis, I perform a battery of additional tests to further distinguish between demand shifts and other 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. By

[14] Specifically, I estimate two cross-sectional regressions each month: (1) $\text{DUAL}_{i,t} = a + b\text{TWIN}_{i,t} + \varepsilon^{\text{DUAL}}_{i,t}$; and (2) $\text{TWIN}_{i,t} = a + b\text{DUAL}_{i,t} + \varepsilon^{\text{TWIN}}_{i,t}$. The residual DUAL (TWIN) is then defined as $\varepsilon^{\text{DUAL}}_{i,t}$ ($\varepsilon^{\text{TWIN}}_{i,t}$).

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-stock returns is a direct consequence of such statistical correlations. Therefore, I examine the cross-correlations from demand shifts using Fama and MacBeth (1973) 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 such an increase 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 stocks are identified 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 stocks remain significant 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 pricing effect is unlikely to be solely ascribed to existing lead-lag return patterns. I further verify the validity of my findings by incorporating more inter-firm linkages and conducting spanning regressions in the robustness section.

[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.

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 is a *risk-based explanation*. 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 stocks represent plausible estimates of the conditional risk premia, then it is possible that stocks with positively (negatively) correlated characteristics display cross-momentum (reversal). The second explanation is *sluggish information diffusion*. 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 stocks indeed share connected fundamentals and potentially correlated cash-flow shocks, it is unclear why underreaction would lead to reversals for dual stocks. 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 strategies would shed light on the relative importance of demand shifts. 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 the cross-reversal and cross-momentum effects. Second, the identification of dual and twin stocks is based on statistical metrics rather than real economic connections. Therefore, the autocorrelation in 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 cross-predictability effects over time should be predictable by macroeconomic conditions. Finally, if the pricing result is driven by underreaction or time-varying risk premia, then the associated abnormal returns should be persistent. Instead, if demand shifts lead to prices deviating from fundamentals, then the strategy returns should eventually reverse.

To examine the role of macroeconomic conditions, I conduct time-series regressions of strategy returns on lagged macro-related variables.[16] Table 5 shows that variables related to macroeconomic conditions lack predictive ability. For the dual strategy, 7 out of 10 estimated coefficients have t-statistics smaller than 1 in absolute value. The performance

[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.

of the dual 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 strategy, except that the coefficient on lagged cross-sectional premium (CSP) is significant (t-stat=2.12). This difference aligns with the view that the dual strategy provides a clearer representation of the impact from demand shifts. The twin strategy, by construction, might contain other confounding mechanisms discussed earlier. Nonetheless, macroeconomic conditions are not likely to be the main force behind the documented pricing effects.

Figure 3 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 demand-shifts story, whereas neglecting fundamental news or the risk-based explanation is less important in driving the results.

4.4 Spanning tests

A fast-growing literature documents a prevailing cross-firm return predictability from economic linkages. 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). While these lead-lag effects are primarily driven by investor underreaction, the cross-predictability in this paper is more consistent with a price pressure story. However, there could be mechanical connections between economic linkages and demand shifts that also contribute to the predictive ability of dual- and twin-stock 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 stocks. While it remains unclear whether the definition of dual stocks can be explicitly linked to economic connections, statistical correlations between signals might still drive both cross-reversal and cross-momentum in this paper.

To address this concern, I conduct additional spanning tests to assess the robustness of

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

my results.[18] Table 11 reports the results from time-series spanning regressions. It shows that the returns associated with DUAL and TWIN remain significant after controlling for several prevailing lead-lag effects. This result suggests that demand shifts provide incremental information about return autocorrelations beyond conventional inter-firm linkages.

Furthermore, many lead-lag patterns are subsumed by demand-shifting effects. For instance, when controlling for shared analyst coverage (CF RET) as in Ali and Hirshleifer (2020), the cross-reversal strategy exhibits a preserved abnormal return of -0.545% (t-stat=-3.19). In contrast, the CF RET strategy produces an alpha of only -0.062% (t-stat= -0.30) after accounting for the DUAL strategy return. One possible interpretation for this finding is that the propagation of demand shocks partially drives lead-lag relations among linked stocks. For instance, Burt and Hrdlicka (2021) and Li and Yan (2024) show that a significant proportion of cross-predictability among economically linked firms can be attributed to their commonality in characteristics-based factors. My theory suggests that one source of such commonality is firms' shared exposure to demand shocks from characteristics-driven investment. In this regard, this paper points to a demand-based perspective on the price interdependence of economically connected firms.[19]

5 Institutional trading and attention

To further investigate the mechanism underlying the return predictability result, this section examines institutional investors' trading and attention. First, I examine institutions' trading in relation to returns of dual and twin stocks. Next, I study the role of institutional investor attention by exploring the time variation in cross-predictability. Lastly, I show that competing assets introduce distraction in the cross-section.

[18] 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.

[19] To the extent that correlation in characteristics overlaps with economic connectedness, this paper's theory can also apply to the spillover effect in economic networks. In fact, one can replace the characteristic matrix Θ in Section 2 with any matrix capturing economic connections among firms. Denote this matrix by $\mathbf{M}$, where $M_{i,j}$ measures the connectedness between firms i and j. Consider the case of industry momentum. We may set $M_{i,j} = 1$ if firms i and j belong to the same industry and $M_{i,j} = 0$ otherwise. The demand-shifts story naturally predicts that economically connected stocks exhibit positive short-term cross-autocorrelation in returns. Moreover, the mechanism implies that this predictability should weaken and eventually reverse over the long run. Li and Yan (2024) indeed find that many cross-predictability anomalies among economically connected stocks display long-term reversal, providing additional empirical support for this paper's theory.

5.1 Institutional trading on dual- and twin-stock returns

The primary mechanism underlying the predictability result, as illustrated in Proposition 1 in Section 2, is the shift in investor demand. In particular, when twin stocks have done well, investors lean toward increasing their positions in the focal stock. Conversely, if dual stocks become attractive, investors tend to reduce holdings in the focal stock and rotate into these assets.

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

$$\Delta Inst_{i,t+1} = a + b_{signal} Signal_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1}, \tag{14}$$

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 return of dual or twin stocks ($Signal_{i,t}$). If investors indeed shift demand between dual and twin stocks, we would observe institutions trading these signals 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-stock returns. 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 demand shifts, the degree of shifting should be more pronounced for institutions with highly active trading strategies. For example, while exchange-traded funds (ETFs) and market index funds also employ specialized investment, variations in the passive ownership should be less responsible for the documented cross-predictability. If anything, the potential positive feedback trading from these institutions should contribute to the within-index momentum rather than cross-reversals. Institutions employing index-based trading strategies are also constrained by the need to maintain tracking errors within certain bounds, which limits their ability to shift toward other characteristics.

To examine the role of active investment, I further partition institutions into different types based on the *Institutional Investor Classification* from Brian Bushee's website (Bushee, 2001;

Bushee and Noe, 2000).[20] 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).[21] For each type of institutional investor, I calculate changes in ownership and perform analogous regressions as in equation (14) to investigate the propensity of demand shifts.

Table 7 presents the results. It shows that independent investment advisors are the primary contributors to the patterns in Table 6. A one-standard-deviation increase in lagged dual-stock returns is associated with a decrease in focal stocks' IIA ownership of around 0.053%, whereas an increase in twin-stock returns implies IIA purchasing focal stocks (with an estimated coefficient of 0.057). Both effects are highly significant. In general, IIA include wealth management companies, hedge funds, private equities, and other professional firms specialized investment strategies. This result aligns with the hypothesis that active institutions engaging in demand shifts 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). Wermers (2012) and Frijns et al. (2016) find that active mutual fund managers engage in index-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 characteristic level. This evidence lends support to my findings.

Investment companies also trade 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-stock 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 and are constrained by institutional mandates. As mentioned earlier, while index funds and ETFs indeed specialize in category-based investment, their incentives and ability to switch are less pronounced compared to highly active institutions. Even for theme-specific mutual funds, the need to maintain low tracking errors prevents them from deviating significantly from market weights. For other institutional investors, Table 7 shows that banks and pension funds do not trade on dual- and twin-stocks' performance. Insurance companies and other institutions exhibit a weak tendency toward demand shifts but the estimated coefficients are not distinguishable from zero.[22] These results also accord with Koijen et al. (2023) that

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

[21]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.

[22]As a robustness test, I also examine the trading of institutional investors based on their activeness.

hedge funds and small-active investment advisors are more influential for equity pricing, whereas long-term investors such as pension funds and insurance companies have relatively small impacts.

5.2 Institutional attention and time variation

Institutional investors play a dominant role in characteristics-based investing. As shown in Section 5.1, highly active institutions exhibit a stronger tendency to shift investments. These findings suggest that cross-firm reversals and momentum would be stronger following periods when institutional investors are more attentive to the market. 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 8, 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

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 of demand shifts, whereas institutions classified as dedicated or quasi-indexer do not actively engage in demand shifts. Notably, Cremers and Pareek (2015) also find that short-term trading likely drives price inefficiency. This result further differentiates my findings from alternative explanations, such as institutional investment constraints (e.g., Cao et al. (2017)), benchmarking (e.g., Pavlova and Sikorskaya (2023)), and common passive ownership (Ying, 2024). If the trading behavior examined in this section is primarily driven by constraints such as maintaining tracking errors, inelastic demand from benchmarking capital, or sluggish information diffusion due to passive investment, then the result should be more pronounced for quasi-indexers rather than transient institutions.

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

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' shifting demand is responsible for the documented cross-predictability.

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 Huang (2019), instead of institutional investors' shifting demand. To address this concern, I conduct predictive regressions using AIA and control for the effect of retail attention. Specifically, retail investor 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 8 reports the regression results. Consistent with the findings in Panel A, AIA negatively predicts subsequent DUAL strategy returns while positively predicting TWIN strategy returns. As a comparison, ARA does not exhibit any predictive ability. 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 hypothesis that retail investors' demand drives the cross-predictability of dual and twin stocks.[24] In addition, investor sentiment exhibits no predictive power, implying that my result is unlikely to be driven by persistence in market sentiment. While validating the role of institutional investors, these findings also indicate that the mechanism behind the documented predictability differs from those identified in previous studies.

5.3 Distraction by competing assets

Another implication of the demand shifts pertains to how investors' attention is shaped by characteristics-based competitive relationships among stocks. As examined in Section

[24]Crucially, Huang (2019) find that due to the experience effect, retail investors tend to purchase stocks in categories where they have previously succeeded. This channel implies that ARA rather than AIA should exhibit predictive power. In sharp contrast, Table 8 suggests that retail investor attention plays only a minor role in the pricing effect.

5.1, demand shifts away from (toward) the focal stock when DUAL becomes attractive (undesirable). In other words, dual stocks compete for capital. An alternative interpretation of this trading behavior is that the demand shifts might merely reflect the rebalancing of quant strategies or mechanical overlaps with passive investing, thus being unrelated to active asset management. If my main results are driven by such *automatic* effects, then the performance of dual and twin stocks should not influence investors' attention toward the focal stock. In contrast, the demand shifts story suggests that attention tends to be redirected away from the focal stock and drawn to the competing (i.e., dual) stocks.

To investigate variations in the allocation of investors' attention, I estimate the following regression:

$$InstAttention_{i,t+1} = a + b_{signal}|Signal_{i,t}| + Controls_{i,t} + \varepsilon_{i,t+1}, \tag{15}$$

where the dependent variable is institutional investors' attention to the focal stock i in month $t+1$. As in the previous section, I use Bloomberg's daily maximum readership (Ben-Rephael et al., 2017) and calculate average values within a month to measure institutional attention. The main independent variable of interest, $|Signal_{i,t}|$, denotes the absolute value of the lagged return of dual or twin stocks. The prediction derived from the demand-shift framework is that the magnitude of DUAL should be *negatively* associated with investors' attention to the focal stock, representing a distraction by competing stocks.

Table 9 reports the regression results. The first two columns show that the estimated coefficient on the magnitude of DUAL is significantly negative, consistent with the notion that variations in the performance of competing stocks distract investors' attention from the focal stock. Columns (3) and (4) examine the effect of twin stocks, suggesting a positive relationship between attention and the return magnitude of stocks that share positive correlations in characteristics. Moreover, columns (5) and (6) show that DUAL dominates TWIN in affecting investor attention, indicating that distraction by competing stocks plays a more critical role than potential attention spillover from similarity in characteristics.[25] Aligning with this result, the robustness test presented in Table 3 also suggests that DUAL surpasses TWIN in terms of predictive power for returns. As such, these findings underscore the necessity of identifying dual stocks and highlight the unique feature of demand-induced price impacts.

[25]It is worth noting that Section 5.2 examines the role of *aggregate* institutional attention, while this section shows that performance of dual and twin stocks influences subsequent attention through cross-sectional analysis. The regression results presented in Table 9 suggest a *redirection* effect rather than fluctuations in the overall level of attention. Additionally, the observed negative relationship between the magnitude of DUAL and institutional attention cannot be easily reconciled with a pure underreaction story. If the return predictability associated with dual stocks reflects the sluggish dissemination of fundamental information, then |DUAL| would be positively associated with the attention measure as institutional investors correcting the initial mispricing of focal stocks.

6 Additional tests

This section provides several robustness tests. First, I examine the trading patterns of short sellers and retail investors. Then, I assess the robustness of the return predictability result to alternative specifications of dual and twin stocks.

6.1 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 stocks. However, less is known about whether professional traders engage in demand shifts 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, I investigate whether the trading behavior of short sellers aligns with demand shifts. 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 trading 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 variation in retail investors' demand.

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).[26] 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 10 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

[26]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/`

holding periods. This computation is analogous to the method employed in Section 4.3. Panel A shows that short sellers tend to increase (decrease) short positions in stocks that have high (low) DUAL signals. Their trading is most pronounced over a 6-month to 12-month period, followed by a slowdown in trading. This pattern is consistent with the long-term pricing result depicted in Figure 3, 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 twin stocks, 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 in longer horizons. Overall, the trading behavior of short sellers aligns with the prediction of demand shifts.

Panels C and D of Table 10 present the results of retail trading. I find that retail investors purchase focal stocks more when the twin-stock return is high or when dual stocks performs poorly. On average, attractive dual-stock returns or disappointing twin-stock returns are not associated with net retail selling. Distinct from the trading of short sellers, the difference in retail trading between high- and low-signal portfolios is significant only over the long horizon. While this result supports the notion of demand shifts, the trading trend appears less consistent compared to that observed among short sellers. In particular, 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 3. This prolonged retail enthusiasm is consistent with the finding of McLean et al. (2020) that individual investors continue their trading tendency for a long period after the time of anomaly portfolio formation.

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

6.2 Alternative specifications of dual and twin stocks

6.2.1 Signals orthogonal to the short-term reversal effect

It is well-documented that stock returns tend to exhibit reversals at short horizons.[27] Although demand shifts give rise to a rich set of predictions regarding cross-correlations, the story is almost silent on explaining short-term own-autocorrelations. In fact, the short-term reversal effect is predominantly interpreted as compensation for providing liquidity (e.g.,

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

Avramov et al. (2006); Nagel (2012); and Dai et al. (2024)). 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 stocks 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-stock 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.

6.2.2 Parameter choice and weighting scheme

The empirical implementation of dual and twin stocks 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. In addition, I explore alternative weighting schemes. 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-stock returns significantly and negatively predict focal stocks' subsequent returns, whereas twin-stock returns exhibit strong and positive predictive power.

6.2.3 Alternative combinations of characteristics

I have thus far focused on five prevailing characteristics relevant to demand shifts and tested return predictability. To address the concern that my findings are dominated by a few characteristics, I examine results 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 stocks. 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 signals continue to deliver robust cross-firm return predictability, and there is little redundancy among the characteristics.

6.2.4 A placebo test using return correlation-based construction

The definition of dual and twin stocks relies on the correlation between assets in terms of *characteristics*. A counterpart construction is using *return* correlations. For example, demand shifting suggests that characteristics-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 stocks. Although empirically feasible, such an approach would lack robust theoretical foundations. Moreover, while demand shifting implies excess comovement among stocks, the converse does not necessarily hold: excess comovement alone is insufficient to properly define and distinguish between dual and twin stocks.[28]

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

7 Conclusion

This paper studies price dynamics when assets are actively managed based on complex characteristics. By analyzing capital allocation decisions of asset managers employing characteristics-based strategies, I show that demand shifts generate significant price contagion across assets. Theoretically, stocks sharing negative (positive) correlations within the characteristic space are classified as dual (twin), exhibiting cross-reversal (momentum). Empirically, I use a set of prevalent characteristics such as value, profitability, investment, momentum, and volatility to construct dual/twin stocks and find strong cross-correlation in

[28]The demand-shift story is also conceptually different from traditional statistical arbitrage tools such as the "pairs trading" strategy (e.g., Gatev et al. (2006)). First, pairs trading identifies stocks with strong commonality in price trends, while demand shifting focuses on correlations in a complex set of firm characteristics. Second, pairs trading strategies explicitly calculate and trade on price deviations between matched stock pairs, whereas demand shifting does not require such comparisons. Third, pairs trading profits arise from price convergence toward common fundamental values, while demand-shifting returns are generated by prices temporarily diverging from fundamentals due to capital reallocations.

stock returns that aligns with demand shifts.

The documented cross-reversal and cross-momentum are robust to a large set of controls and are consistent with institutional trading patterns. These results suggest that the pervasive adoption of complex equity trading strategies in asset management might in turn exert multifaceted price impacts. In future research, it would be intriguing to study the influence of demand shifts on other market anomalies such as the risk-return trade-off. It would also be valuable to explore the asset pricing implications of demand shifts in other markets such as the bond market, the derivatives market, and the foreign exchange market, as well as the potential cross-market correlations.

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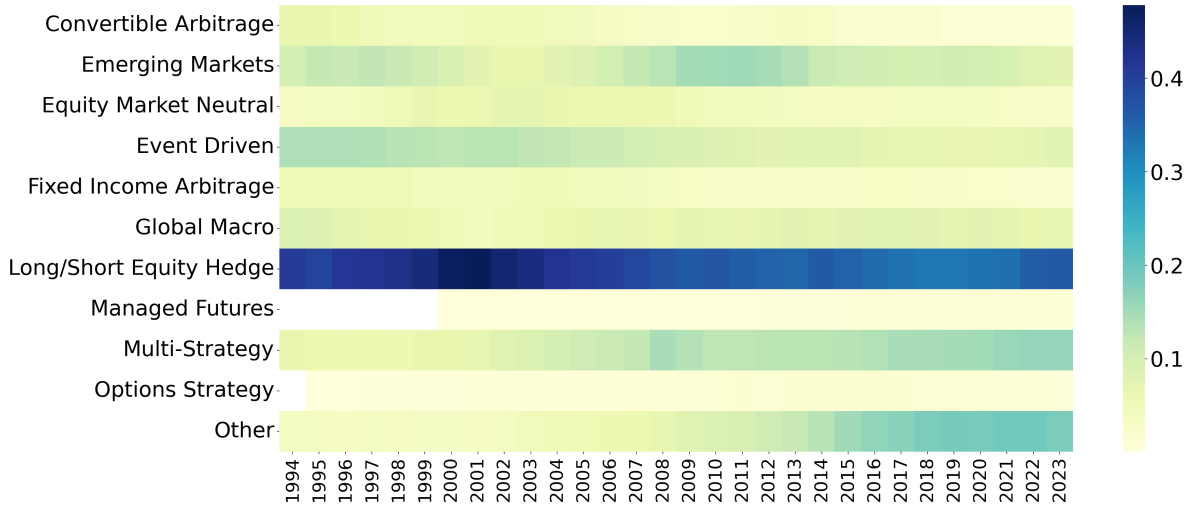


Figure 1. Hedge fund strategy proportions

This figure plots the proportions of U.S. hedge funds classified by strategy categories over time. The data is sourced from the Lipper-TASS database, excluding funds of funds. On average, hedge funds employing the Long/Short Equity Hedge strategy represent 38.7% of the sample.

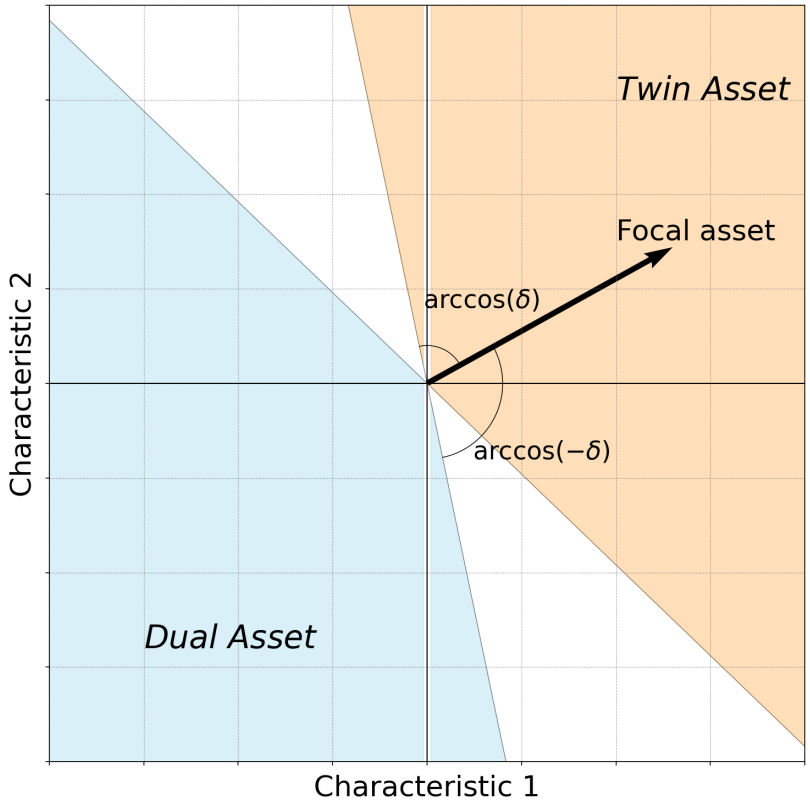


Figure 2. Dual and twin assets
This figure illustrates the concept of dual and twin assets within a two-dimensional characteristic space. For any given focal asset, assets located within the orange region are classified as twin, while those situated within the blue region are identified as dual. The parameter $\delta \in [0, 1)$ balances between the precision and inclusiveness of the empirical construction. The term *arccos* represents the inverse cosine function.

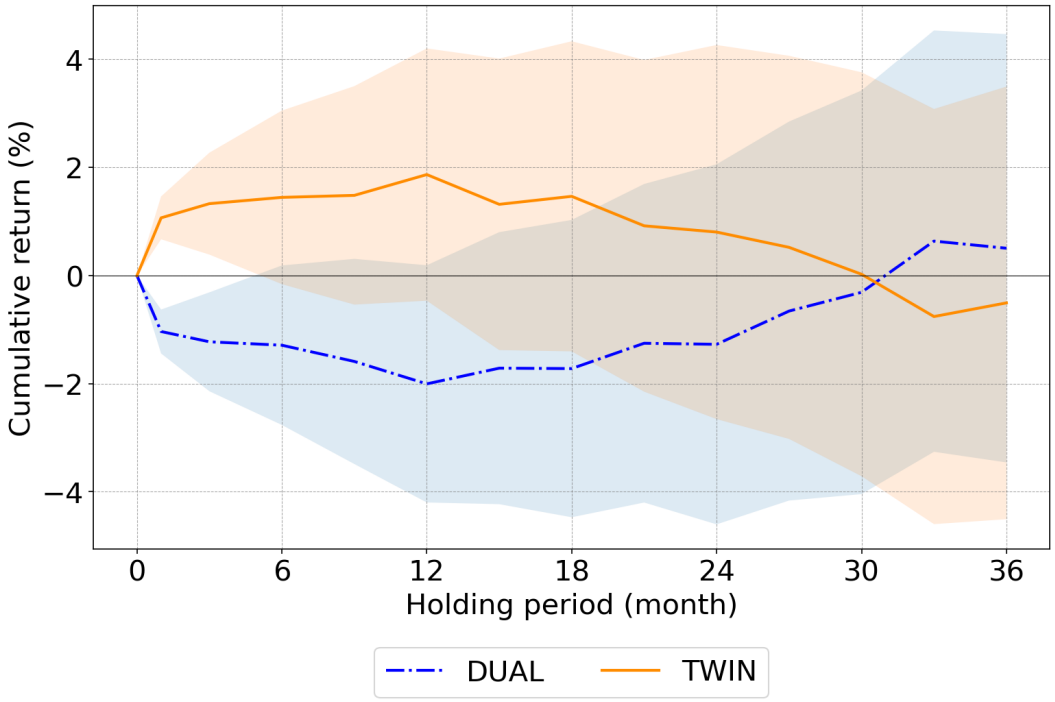


Figure 3. Long-term performance of DUAL and TWIN strategies
This figure plots the average cumulative returns of high-minus-low portfolios based on DUAL (dashed blue line) and TWIN (solid orange line). Strategy returns are market adjusted using CAPM. The shaded areas represent the 95% confidence intervals. The sample period is from July 1963 to December 2021.

Table 1. Summary statistics of DUAL and TWIN portfolios

This table reports summary statistics of portfolios formed on dual-stock returns (Panel A) and twin-stock 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. Firm-specific dual and twin stocks 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) category. 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). RET, MOM, IVol, and ST are presented in percentages. The sample period is from July 1963 to December 2021.

Panel A. DUAL portfolios										
	RET	BM	OPe	AG	VOL	MOM	IVol	Size	ILLIQ	ST
Low	3.75	0.84	-0.17	0.18	0.14	21.13	2.45	12.08	0.48	0.82
2	3.01	0.98	0.02	0.17	0.15	18.44	2.66	11.75	0.70	0.85
3	1.46	0.95	0.08	0.17	0.14	16.06	2.48	11.84	0.60	0.62
4	0.04	0.84	0.18	1.20	0.13	15.03	2.31	12.14	0.52	0.44
High	-0.55	0.72	-0.02	0.17	0.12	14.51	2.03	12.58	0.34	0.26
High-Low	-4.30	-0.12	0.16	-0.01	-0.03	-6.62	-0.42	0.50	-0.14	-0.56
Panel B. TWIN portfolios										
	RET	BM	OPe	AG	VOL	MOM	IVol	Size	ILLIQ	ST
Low	-0.03	0.93	-0.23	0.21	0.15	15.71	2.61	11.65	0.66	0.57
2	0.10	0.76	0.24	1.18	0.12	14.79	2.07	12.52	0.37	0.34
3	1.39	0.75	0.32	0.14	0.10	14.68	1.89	12.81	0.30	0.36
4	2.81	0.85	0.09	0.17	0.13	17.57	2.37	12.14	0.50	0.69
High	3.46	1.03	-0.36	0.20	0.17	22.42	2.97	11.29	0.81	1.03
High-Low	3.48	0.10	-0.13	-0.01	0.02	6.72	0.36	-0.35	0.15	0.46

Table 2. One-sort portfolios based on dual- and twin-stock returns

This table reports portfolio returns based on DUAL (Panel A) and TWIN (Panel B), respectively. 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 (12). Each month, stocks are sorted into quintile portfolios based on DUAL (Panel A) or TWIN (Panel B). Portfolios are held for one month. 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. 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 stocks								
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 stocks								
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)

Table 3. One-sort portfolios based on residual dual- and twin-stock 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 (12). 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-stock return								
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-stock return								
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 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) category, 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), as outlined in Table 1. 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)
Controls	√	√	√	√	√	√	√	√	√	√
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 strategy performance

This table reports time-series regressions of strategy returns on lagged macroeconomic risk variables:

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

The dependent variable $R_{signal,t+1}$ is the monthly value-weighted strategy return based on DUAL or TWIN. $Macro_t$ 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 signal		Twin signal	
	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 returns

This table reports panel regressions of institutional investors' trading on dual- and twin-stock returns:

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

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) 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. Changes in 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	√	√	√	√	√	√
Time FE	√	√	√	√	√	√
Industry FE		√		√		√
N	453295	453287	453295	453287	453295	453287
Adj. R^2	0.09	0.09	0.09	0.09	0.09	0.09
Panel B. Changes 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	√	√	√	√	√	√
Time FE	√	√	√	√	√	√
Industry FE		√		√		√
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-stock returns, where institutions are classified based on the *Institutional Investor Classification* of Brian Bushee:

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

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) 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	√	√	√	√	√	√	√	√	√	√	√	√
Time FE	√	√	√	√	√	√	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√	√	√	√	√	√	√
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. Aggregate institutional attention

This table reports the time variation in 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

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

where $\mathbf{I}_{\text{High},t}$ and $\mathbf{I}_{\text{Low},t}$ are dummy variables indicating high- and low-AIA periods, $R_{signal,t+1}$ is the subsequent strategy return based on DUAL or TWIN, 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

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

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 signal			Twin signal		
	α_H	α_L	$\alpha_H - \alpha_L$	α_H	α_L	$\alpha_H - \alpha_L$
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 signal			Twin signal		
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	√	√	√	√	√	√
N	142	200	130	142	200	130

Table 9. Distraction by dual stocks

This table reports panel regressions of institutional investors' attention on the absolute value of dual- and twin-stock returns:

$$InstAttention_{i,t+1} = a + b_{signal}|Signal_{i,t}| + Controls_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the average institutional attention toward the focal stock i in month $t+1$, measured by Bloomberg's readership data (Ben-Rephael et al., 2017). The independent variable, $|Signal_{i,t}|$, is lagged dual- and twin-stock return in absolute value. Control variables include the log of market capitalization, the log of the book-to-market ratio, the focal stock's past monthly return in absolute value, past 11-month return (skipping the most recent month) in absolute value, asset growth, operating profits, and return volatility. Independent variables are winsorized at 1% and 99% each month and cross-sectionally standardized to have zero mean and unit variance. Regressions include year-month and industry fixed effects. The t-statistics based on standard errors clustered at month and firm levels are reported in parentheses. The sample period is from March 2010 to December 2020 due to constraints on institutional attention data.

	(1)	(2)	(3)	(4)	(5)	(6)
|DUAL|	-0.002	-0.002			-0.002	-0.002
	(-3.46)	(-2.91)			(-3.26)	(-2.65)
|TWIN|			0.001	0.001	0.000	0.000
			(2.23)	(2.07)	(0.42)	(0.69)
Controls	√	√	√	√	√	√
Time FE	√	√	√	√	√	√
Industry FE		√		√		√
N	168721	158379	168721	158379	168721	158379
Adj. R^2	0.37	0.39	0.37	0.39	0.37	0.39

Table 10. Trading of short sellers and retail investors

This table reports the trading by short sellers and retail investors over h months after 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-stock return or the twin-stock return. The high group consists of stocks 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 stocks								
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 stocks								
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 stocks								
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 stocks								
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 11. Spanning tests

This table reports the results from spanning regressions:

$$R_{signal,t} = \alpha_{signal} + \beta R_{link,t} + Controls_t + \varepsilon_{signal,t}$$
$$R_{link,t} = \alpha_{link} + \beta R_{signal,t} + Controls_t + \varepsilon_{link,t}$$

where $R_{signal,t}$ is the monthly strategy return (DUAL or TWIN) and $R_{link,t}$ is the contemporaneous monthly strategy return 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), customer industry momentum (IOCUS RET), supplier industry momentum (IOSUP RET), and shared analyst coverage (CF RET). Intercepts α_{signal} and α_{link} represent the preserved abnormal returns. Control variables include the five asset pricing factors of Fama and French (2015) and a momentum factor. 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. Due to data constraints, the sample periods for these linkage settings start in July 1989, July 1963, July 1963, July 1977, February 1980, January 1986, January 1986, and January 1984, respectively, and end in December 2021.

	DUAL		TWIN	
	α_{signal}	α_{link}	α_{signal}	α_{link}
TIC RET	-0.592	-0.034	0.568	0.048
	(-2.71)	(-0.17)	(2.47)	(0.23)
GEO RET	-0.763	-0.094	0.878	-0.110
	(-4.02)	(-0.93)	(4.92)	(-1.08)
TECH RET	-0.762	-0.075	0.889	-0.069
	(-4.03)	(-0.44)	(4.76)	(-0.38)
PC RET	-0.706	0.077	0.789	0.080
	(-2.95)	(0.45)	(3.38)	(0.44)
CUS RET	-0.716	0.663	0.793	0.696
	(-2.58)	(2.82)	(2.82)	(2.91)
IOCUS RET	-0.961	-0.082	0.944	-0.054
	(-3.35)	(-0.44)	(3.41)	(-0.29)
IOSUP RET	-0.907	0.093	0.917	0.163
	(-3.21)	(0.44)	(3.26)	(0.78)
CF RET	-0.545	-0.062	0.531	0.053
	(-3.19)	(-0.30)	(2.51)	(0.22)

Appendix to "Demand Shifts and Asset Pricing"

This Appendix provides a simple extended model to characterize the dynamics of equilibrium asset prices (Appendix A1), supplementary empirical results omitted from the paper for brevity (Appendix A2), and details on the construction of other inter-firm linkage variables (Appendix A3) .

A1 A simple characterization of equilibrium asset prices

Consider the economy presented in Section 2 of the paper. In addition to the quant trader, we introduce a *fundamental investor* who focuses on expected dividends of risky assets (Shleifer and Vishny, 1997; Barberis and Shleifer, 2003; Barberis et al., 2018) . Specifically, the fundamental investor's portfolio choice problem is given by the standard form without assumptions on its investment strategy:

$$\max_{\mathbf{N}_t^f} \mathbb{E}_t^f(\mathbf{P}_{t+1} - \mathbf{P}_t)'\mathbf{N}_t^f - \frac{\gamma_f}{2}(\mathbf{N}_t^f)'\mathbf{V}\mathbf{N}_t^f, \tag{A1.1}$$

The first-order condition implies that the demand of the fundamental investor is:

$$\mathbf{N}_t^f = \frac{1}{\gamma_f}\mathbf{V}^{-1}\mathbb{E}_t^f[\mathbf{P}_{t+1} - \mathbf{P}_t]. \tag{A1.2}$$

Assuming a fixed supply of risky assets $\mathbf{Q} = (Q_1, ..., Q_N)$, the market clearing condition is given by

$$\mathbf{N}_t^q + \mathbf{N}_t^f = \mathbf{Q},$$

where $\mathbf{N}_t^q = \frac{1}{\gamma_q}\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'\mathbb{E}_t^q[\mathbf{P}_{t+1} - \mathbf{P}_t]$ is the demand of the quant trader. Consequently, the equilibrium price is characterized by

$$\mathbf{P}_t = \mathbb{E}_t^f[\mathbf{P}_{t+1}] - \gamma_f\mathbf{V}(\mathbf{Q} - \mathbf{N}_t^q), \tag{A1.3}$$

which requires specifying the belief of the fundamental investor (i.e., $\mathbb{E}_t^f[\cdot]$) to yield an analytical solution. I use backward induction to solve the prices.

In period $T-1$, the belief is characterized by $\mathbb{E}_{T-1}^f[\mathbf{P}_T] = \mathbb{E}_{T-1}^f[\mathbf{D}_T] = \mathbf{D}_{T-1}$, implying that the fundamental investor's demand is $\mathbf{N}_{T-1}^q = \frac{1}{\gamma_f}\mathbf{V}^{-1}(\mathbf{D}_{T-1} - \mathbf{P}_{T-1})$. It follows that the price in period $T-1$ is

$$\mathbf{P}_{T-1} = \mathbf{D}_{T-1} - \gamma_f\mathbf{V}(\mathbf{Q} - \mathbf{N}_{T-1}^q).$$

Consequently, the price in period $T-2$ is:

$$\begin{aligned}\mathbf{P}_{T-2} &= \mathbb{E}^f_{T-2}\left[\mathbf{D}_{T-1} - \gamma_f \mathbf{V}(\mathbf{Q} - \mathbf{N}^q_{T-1})\right] - \gamma_f \mathbf{V}(\mathbf{Q} - \mathbf{N}^q_{T-2}) \\ &= \mathbf{D}_{T-2} + \gamma_f \mathbf{V}\mathbb{E}^f_{T-2}[\mathbf{N}^q_{T-1}] - 2\gamma_f \mathbf{V}\mathbf{Q} + \gamma_f \mathbf{V}\mathbf{N}^q_{T-2},\end{aligned} \tag{A1.4}$$

where the second equality holds since $\mathbb{E}^f_{T-2}[\mathbf{D}_{T-1}] = \mathbf{D}_{T-2}$.

Equation (A1.4) suggests that, in addition to fundamental shocks (i.e., $\mathbf{D}_{T-2}$), the dynamics of the equilibrium price are determined by two components: (1) demand shocks from the quant trader's active strategy, $\mathbf{N}^q_{T-2}$; and (2) the fundamental investor's belief about the quant trader's demand, $\mathbb{E}^f_{T-2}[\mathbf{N}^q_{T-1}]$. In other words, equilibrium prices are set as the fundamental investor takes into account the demand shock from the quant trader. Given that the quant trader's trading strategy is highly complex (captured by the coefficients $\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'$), we assume that the fundamental investor is relatively passive and less sophisticated, specifically $\mathbb{E}^f_t[\mathbf{N}^q_{t+1}] = \bar{\mathbf{N}}^q$. That is, the fundamental investor's belief about the quant trader's demand is constant. An interpretation of this assumption is that the fundamental investor partially absorbs demand shocks from demand shifts, preventing prices from deviating too much from fundamental values (expected dividends). Recent studies such as Cui et al. (2024) indeed provide evidence that passive and low turnover institutions tend to trade in the opposite direction of hedge funds.

Iterating as in equation (A1.4) yields

$$\mathbf{P}_t = \mathbf{D}_t + \frac{\gamma_f}{\gamma_q}\mathbf{V}\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'\mathbb{E}^q_t[\mathbf{P}_{t+1} - \mathbf{P}_t] - (T-t)\gamma_f \mathbf{V}\mathbf{Q} + (T-t-1)\gamma_f \mathbf{V}\bar{\mathbf{N}}^q. \tag{A1.5}$$

Let $\mathbf{R}_t = \mathbf{P}_t - \mathbf{P}_{t-1}$ be the vector of returns and denote $\frac{\gamma_f}{\gamma_q}\mathbf{V}\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'$ by Ψ for simplicity of notation. We have

$$\mathbf{R}_t = \varepsilon_t + \Psi\left\{\mathbb{E}^q_t[\mathbf{R}_{t+1}] - \mathbb{E}^q_{t-1}[\mathbf{R}_t]\right\} + \gamma_f \mathbf{V}(\mathbf{Q} + \bar{\mathbf{N}}^q), \tag{A1.6}$$

where $\varepsilon_t = \mathbf{D}_t - \mathbf{D}_{t-1}$ by definition is the vector of dividend shocks. Note that the quant trader's belief is given by $\mathbb{E}^q_t[\mathbf{R}_{t+1}] = (1-\theta)\sum_{l=1}^{t-1}\theta^{l-1}\mathbf{R}_{t-l} + \theta^{t-1}\mathbf{X}_1$, we have

$$\mathbb{E}^q_t[\mathbf{R}_{t+1}] - \mathbb{E}^q_{t-1}[\mathbf{R}_t] = (1-\theta)\mathbf{R}_{t-1} - (1-\theta)^2\sum_{l=1}^{t-2}\theta^{l-1}\mathbf{R}_{t-l-1} + \theta^{t-2}(\theta-1)\mathbf{X}_1. \tag{A1.7}$$

Therefore, the process of risky assets' returns is given by

$$\mathbf{R}_t = \varepsilon_t + (1-\theta)\Psi\left[\mathbf{R}_{t-1} - (1-\theta)\sum_{l=1}^{t-2}\theta^{l-1}\mathbf{R}_{t-l-1} - \theta^{t-2}\mathbf{X}_1\right] + \gamma_f \mathbf{V}(\mathbf{Q} + \bar{\mathbf{N}}^q). \tag{A1.8}$$

Equation (A1.8) makes it clear that the covariances between risky assets' returns depend on their correlations in the characteristic space (captured by $\Psi = \frac{\gamma_f}{\gamma_q}\mathbf{V}\Theta(\Theta'\mathbf{V}\Theta)^{-1}\Theta'$). In the short term, dual (twin) assets exhibit negative (positive) cross-autocorrelations in the presence of demand shifts. In the long run, the covariances tend to reverse as prices converge to fundamental values.

In particular, one obtains factor momentum (Lewellen, 2002; Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023; Yan and Yu, 2023) by left-multiplying $\mathbf{R}_t$ by the characteristic matrix:

$$\Theta'\mathbf{R}_t = \varepsilon_t + \frac{\gamma_f}{\gamma_q}(1-\theta)\Theta'\left[\mathbf{R}_{t-1} - (1-\theta)\sum_{l=1}^{t-2}\theta^{l-1}\mathbf{R}_{t-l-1} - \theta^{t-2}\mathbf{X}_1\right] + \gamma_f\Theta'\mathbf{V}(\mathbf{Q}+\bar{\mathbf{N}}^q). \quad \text{(A1.9)}$$

A novel prediction of equation (A1.9) is that factor momentum should eventually *reverse* at longer horizons, echoing the empirical evidence in Favero et al. (2023) and Li and Yan (2024).

A2 Additional empirical results

Table A1 reports panel regression results of the trading of low-active and high-active institutions. 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) signals orthogonal to the short-term reversal effect; (2) dual and twin stocks constructed using different δ values; and (3) equal-weighted and absolute cosine similarity-weighted signals.

Table A3 reports strategy returns, where dual and twin stocks are identified 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 signals, where pseudo-dual and pseudo-twin stocks are constructed based on return correlations.

A3 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.[29] 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 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.[30] 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.

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

[30] `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-stock returns, where institutions are classified based on the *Institutional Investor Classification* of Brian Bushee:

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

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) 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	√	√	√	√	√	√	√	√	√	√	√	√
Time FE	√	√	√	√	√	√	√	√	√	√	√	√
Industry FE		√		√		√		√		√		√
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 signal, parameter choice, and weighting scheme

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 dual- and twin-stock returns. Residual 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 stocks; in the last two columns, δ is set at 0.25, while signals are calculated based on equal-weighted (EW) or absolute cosine similarity-weighted (CW) average returns of stocks within the dual/twin category. 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 stocks from alternative characteristic combinations

This table reports the average returns of strategies based on DUAL and TWIN. The set of characteristics includes the book-to-market ratio (BM), operating profits (OPe), 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, dual and twin stocks are formed using characteristic pairs. For instance, the cell (AG, OPe) shows the average TWIN strategy return, with twin stocks identified using asset growth and operating profits; the cell (OP, MOM) indicates the average DUAL strategy return, where dual stocks are determined using operating profits and momentum. In Panel B, dual and twin stocks are constructed using three characteristics. For example, cell (AG, OPe) displays the average TWIN strategy return, with twin stocks constructed based on characteristics excluding asset growth and operating profits. In Panel C, dual and twin stocks are formed using four characteristics, with each column displaying results from excluding the corresponding characteristic. For instance, column BM represents the average strategy returns of DUAL and TWIN, where dual and twin stocks 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. Dual and twin stocks from characteristic pairs					
TWIN\DUAL	BM	OPe	AG	MOM	VOL
BM	-	-0.398	-0.571	-0.433	-0.929
		(-3.19)	(-4.15)	(-3.10)	(-4.51)
OPe	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. Dual and twin stocks from excluding characteristic pairs					
TWIN\DUAL	BM	OPe	AG	MOM	VOL
BM	-	-0.958	-0.950	-0.998	-0.565
		(-4.52)	(-4.46)	(-5.05)	(-3.71)
OPe	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. Dual and twin stocks from excluding one characteristic					
	BM	OPe	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-stock returns

This table reports portfolio returns based on pseudo dual- and twin-stock returns. For each stock, the pseudo dual stocks and the pseudo twin stocks 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) category. 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-stock 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-stock 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-stock 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)