

Dual peer effects and cross-stock predictability[☆]Doron Avramov^a, Shuyi Ge^b, Shaoran Li^c, Oliver Linton^d^a Reichman University (IDC Herzliya), Israel^b School of Finance, Nankai University, China^c School of Economics, Peking University, China^d Faculty of Economics, University of Cambridge, United States of America

ARTICLE INFO

Dataset link: [dual peer effect dataset \(Original data\)](#)

JEL classification:

G11

G12

G14

Keywords:

Cross-stock predictability

Peer effect

Asset pricing

Economic links

Information aggregation

ABSTRACT

This paper introduces a Peer Index (PI) constructed from economically motivated peer networks that summarizes (i) the strength of a firm's peers and (ii) the firm's position within its peer group. PI predicts stock returns and earnings surprises over short and long horizons. Machine-learning models based solely on firm-level characteristics do not subsume PI's predictive power, supporting the interpretation that it captures genuine cross-stock information. Lag-augmented local projections show that positive PI innovations are followed by higher next-month returns that gradually decay without reversal, consistent with slow diffusion of peer information into prices.

1. Introduction

Understanding which firm attributes explain the cross-section of average returns is a cornerstone of empirical finance. While most research has focused on firm-own characteristics to predict future returns, it has largely overlooked the potential of *cross-predictability*—leveraging characteristics of one firm to forecast the returns of another. Recently, Kelly et al. (2023) introduced comprehensive methodologies for exploring cross-stock predictability, underscoring the substantial yet underutilized potential of this approach.

To fully capitalize on this potential, we highlight two challenges. First, from an economic perspective, firms operate within networks of peers shaped by shared economic, operational, and regulatory environments. These interconnections can contain predictive information not explicitly embedded in firm-only characteristics. Second, from an

econometric perspective, conventional models that regress future returns on lagged predictive characteristics may obscure the role of network effects in shaping individual firm outcomes.

To illustrate, consider the standard cross-sectional regression of future stock returns $r_{i,t+1}$ on lagged returns $r_{i,t}$, where t denotes time and i indexes stocks. This univariate specification can be equivalently rewritten by decomposing the lagged return into its peer-group average $\bar{r}_{I,t}$, where I indexes the peer group, and the firm-level deviation $r_{i,t} - \bar{r}_{I,t}$. Standard cross-sectional regressions implicitly impose the restriction that the slope coefficients on the peer-group average and on the within-peer deviation are identical. Relaxing this restriction reveals important empirical regularities. For example, for one-month past returns, the industry peer-group average carries a positive coefficient (industry momentum), while the deviation carries a negative coefficient (short-run reversal within industries and across stocks). A similar inference

[☆] We thank Jonathan Lewellen, Robert Stambaugh, Dimitris Papanikolaou, Lin Peng, Jianfeng Yu, Andreas Neuhierl, Mark Grinblatt, Jeremiah Green, Hong Xiang, and an anonymous referee for helpful comments and suggestions. We also thank participants at the 2024 AsianFA Meeting, the 2024 China International Risk Forum, the China Finance Review International Joint Conference, and the 5th Greater China Area Finance Conference for valuable feedback. Shuyi Ge is supported financially by National Natural Science Foundation of China (project code No. 72303119, 72495150, 72495155); Shaoran Li acknowledges the financial support from National Natural Science Foundation of China (project code No. 72573004, 72203007) and School of Economics, Peking University, China. The usual disclaimers apply.

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¹ See, e.g., Lewellen (1999), who study the information content of the book-to-market ratio.

obtains when peer groups are defined by supply-chain networks in the presence of momentum spillovers (e.g., [Cohen and Frazzini \(2008\)](#)). The meaningful role of peer groups in the cross-section extends beyond past returns to other predictive characteristics.¹

To address these challenges, we develop a systematic framework that captures *dual peer effects* in cross-stock predictability. At its core is the *Peer Index (PI)*—a synthesized metric that quantifies both (i) the collective strength of a firm's peer group and (ii) the firm's relative position within that group. In our main analysis, we define peers using Standard Industrial Classification (SIC) codes. Industry classifications have long been a cornerstone of empirical research, and their stability over time makes them especially well suited for long-horizon analyses of market reactions to peer-related information. While the industry-based network is symmetric by construction — if firm i is in the same industry as firm j , then firm j is a peer of firm i — we also analyze two alternative peer networks based on customer–supplier links and analyst co-coverage. We consider these asymmetric networks both for robustness and to examine the roles of the factor-neutral “alpha” component and the factor-exposure “beta” component via the symmetric–antisymmetric decomposition of [Kelly et al. \(2023\)](#).

We construct PI using ridge regressions that include both peer-average characteristics and firm-level deviations. Ridge regressions are known to perform well in high-dimensional, low-signal-to-noise environments ([Kelly et al., 2024](#); [Shen and Xiu, 2025](#)), and the framework extends readily to richer nonlinear estimators. The ridge fitted values define PI—our proxy for expected returns that captures dual peer effects in asset prices.

Using the comprehensive characteristics dataset compiled by [Jensen et al. \(2023\)](#), covering January 1980 through December 2024, we show that PI aggregates information from a wide set of peer averages and within-peer deviations. Beyond past-return variables, quality, value, and profitability measures contribute materially to the index. Moreover, PI is only weakly correlated with any individual input, indicating that its predictive content reflects breadth rather than dominance by a single characteristic. The coefficient signs from the underlying ridge regressions further indicate that high-PI stocks tend to belong to stronger industry peer groups and are well positioned within their peer networks.

When PI is added to the value-weighted cross-sectional regressions, four major past-return and industry-related anomalies become insignificant, while PI itself remains strongly significant ($t = 5.71$). Its predictive content is robust to (i) excluding microcaps, (ii) restricting the sample to recent years, and (iii) conditioning on both contracting and expanding market states. Moreover, PI's reach is not confined to the short run: over a three-year horizon, the PI slope coefficient ($\times 100$) equals 8.16 ($t = 2.57$), indicating substantial long-horizon forecasting power. In addition, a nonlinear version of PI — built from nonlinear transformations of the characteristics — delivers incremental explanatory power over the linear PI, suggesting that the dual peer effects persist in richer, more complex information environments.

Portfolio sorts reinforce the predictive power of PI. A value-weighted top-minus-bottom quintile portfolio delivers a monthly excess return of 0.89% ($t = 6.05$). Augmenting the Fama–French five-factor model with momentum and reversal yields a seven-factor alpha of 0.68% ($t = 5.45$). The PI portfolio's alpha persists over extended horizons: with a 12-month holding period, the value-weighted top-minus-bottom portfolio delivers an annualized seven-factor alpha of 2.23% ($t = 8.67$).

To test temporal robustness, we re-estimate our main analyses using only post-2003 data. In value-weighted cross-sectional regressions, PI remains strong across expanding windows and rolling windows of 12, 60, 120, and 360 months. In portfolio tests, the top-minus-bottom value-weighted spreads — and their corresponding seven-factor alphas — remain economically meaningful and statistically significant for one-month and longer holding periods.

Next, we conduct comprehensive factor-spanning tests using PI-based factor as test assets. We consider the Fama–French five-factor model ([Fama and French, 2015](#)); the five-factor model with momentum ([Carhart, 1997](#)), short-term reversal ([De Bondt and Thaler, 1985](#)), and liquidity ([Pástor and Stambaugh, 2003](#)); the Daniel–Hirshleifer–Sun three-factor model ([Daniel et al., 2020](#)); the Hou–Xue–Zhang four-factor model ([Hou et al., 2015](#)); and the Stambaugh–Yuan four-factor model ([Stambaugh and Yuan, 2017](#)). The PI-based factor (PIF) yields economically significant alphas across all specifications. Even in an all-inclusive 14-factor model, PIF retains an alpha of 0.87% ($t = 2.46$), indicating that adding PIF substantially enhances the tangency portfolio's Sharpe ratio.

It should be noted that flexible machine-learning (ML) methods could, in principle, approximate our decomposition using only firm-level characteristics, raising the concern that our results might simply reflect firm-level predictability rather than genuine cross-stock effects. We address this concern in four ways.

First, our approach imposes economically meaningful structure on the return-generating process, yielding an interpretable decomposition into peer averages and within-peer deviations. Generic ML methods, by contrast, search for statistical regularities without economic guidance; there is no reason to expect them to recover our peer-group structure or to sort firms into economically coherent peer sets. Even if deep models could approximate such structure after extensive tuning, without these restrictions the outcome is neither guaranteed nor computationally practical.

Second, PI remains economically and statistically significant after controlling for flexible ML forecasts. Using three nonlinear methods from [Gu et al. \(2020\)](#) — gradient-boosted regression trees, random forests, and neural networks — we construct expected-return controls. In Fama–MacBeth regressions that include these ML forecasts, PI remains robust. Out of sample, adding PI improves fit and reduces the standard deviation of forecast errors relative to the ML benchmarks. In portfolio and spanning tests, we orthogonalize PI to the ML forecasts (retaining the alpha plus residual) and still obtain sizable, significant performance that is not explained by a broad set of known factors.

Third, PI predicts future earnings surprises at both short and long horizons, even after conditioning on ML-based return predictors. This shows that PI captures economically relevant information beyond firm-specific return patterns—information that even professional analysts appear to overlook.

Fourth, our linear, regularized implementation provides a conservative benchmark. As a preliminary check, we construct a nonlinear version of PI by applying polynomial transformations to the PI constituents and find that this nonlinear PI delivers incremental explanatory power over the linear PI. This finding is in line with [Didisheim et al. \(2024\)](#) and highlights the value of allowing for nonlinearities in asset-pricing frameworks. Any additional accuracy delivered by richer nonlinear estimators would only strengthen our results, so the evidence reported here should be viewed as a lower bound on PI's predictive content.

Thus, the overall evidence shows that PI extracts information not recoverable from firm-only characteristics using off-the-shelf ML, isolating genuine cross-stock structure rather than rediscovering purely firm-level effects.

To connect the cross-sectional profitability of PI to the underlying price-formation mechanism, we take a dynamic perspective on how peer-based information is absorbed. Building on the shock-and-response logic of [Kogan and Papanikolaou \(2013, 2014\)](#), and adapting the recent lag-augmented local projections (LA-LP) framework from [Montiel Olea and Plagborg-Møller \(2021\)](#) to our setting, we estimate the impulse response of stock returns to an innovation in PI. A ten-percentile increase in PI is followed by an immediate rise of about 0.4% in the next month, and the effect then decays over the subsequent months *without* reversing. This pattern is consistent with a slow-diffusion view of peer information: prices move in the correct direction on impact, the adjustment is spread over several months, and

there is no subsequent undoing of the initial reaction. The dynamic evidence therefore links the cross-sectional results to a clear time-series channel through which peer information is incorporated into prices.

We interpret these findings as evidence that markets underweight peer-relevant information. PI jointly captures (i) the overall strength of a firm's peer group and (ii) the firm's position relative to that group; combining these two sources produces a forward-looking signal that is only partially processed by investors, who tend to focus on firm-specific metrics and, to a lesser extent, broad peer aggregates. Consistent with this interpretation, PI is positively related to contemporaneous and future industry-level earnings surprises and predicts future stock returns; at the firm level, PI likewise forecasts earnings surprises and returns. Thus, the cross-sectional and dynamic results line up on the same underreaction channel.

To rule out competing explanations, we show that the PI effect does not appear to be a reward for risk, nor is it driven by sentiment. High-PI stocks do not load more heavily on standard factors, do not exhibit unusually high downside risk, and do not concentrate returns in particular business-cycle states. The return differential persists for up to three years and does so *without* long-run reversal, which is hard to reconcile with a temporary overreaction story. Moreover, PI remains predictive after controlling for stock- and industry-level sentiment and within both high- and low-sentiment subsamples, indicating that attention- and sentiment-based channels cannot fully account for the results.

In our final experiments, we study two asymmetric networks — shared-analyst coverage and customer-supplier links — and uncover two additional findings. First, PI remains economically and statistically significant in cross-sectional regressions that augment our baseline specification with variables capturing these networks, indicating that the cross-stock predictability we document is not merely a reflection of momentum transmitted through analyst co-coverage or supply chains. Second, when we decompose the corresponding asymmetric position matrices into symmetric (beta-like) and antisymmetric (alpha-like) components, we find that the antisymmetric peer-average sleeve — capturing factor-neutral, cross-directional timing — emerges as a key driver of predictability.

These patterns suggest that when the peer network is symmetric, cross-stock predictability is captured by the beta-like component, which reflects a combination of peer averages and within-peer deviations that load similarly across firms. By contrast, once the peer graph admits asymmetry — as in supply chains or shared-analyst coverage — the antisymmetric, alpha-like component becomes an important source of predictability, consistent with factor-neutral timing and with information flowing directionally across economically linked firms.

Together, the results underscore the importance of dual peer effects in asset pricing. Standard forecasting approaches typically treat stocks as independent rather than as nodes in an economic network. Existing peer-effects studies usually focus on narrow channels (e.g., peers' past returns) and thus miss the richer interdependencies embedded in peer relationships. This omission contributes to persistent underreaction to information in peer linkages, leading to slow price adjustment. The underreaction is stronger when information uncertainty is higher and attention is lower, as we document using analyst-based proxies for uncertainty and news-coverage measures of investor attention.

We recognize that cross-sectional asset pricing is a well-researched field, so distinctiveness matters. Our contribution is to *sharpen* cross-predictability by imposing economic structure on peer information. Three features make the results stand out. First, the effect is robust across market states — sentiment, liquidity, volatility, and trend — whereas earlier work typically finds stronger results only when limits to arbitrage are high (Stambaugh et al., 2012). Second, the effect persists in recent decades, when many prominent anomalies have weakened or disappeared (Chordia et al., 2014). Third, amid concerns about the “factor zoo” and false discoveries (Harvey et al., 2016; Green et al., 2017; Harvey and Liu, 2019; Feng et al., 2020; Chen and Dim, 2023; Da et al., 2024; Chernov et al., 2025), organizing signals into peer

averages and within-peer deviations yields two interpretable channels and a single composite predictor. Evaluated under modern standards — value-weighted Fama–MacBeth with proper microcap treatment (Hou et al., 2020; Green et al., 2017), post-2003 subsamples (Green et al., 2017), long-horizon tests, and extensive factor spanning — PI remains strongly predictive and delivers sizable alpha.

Our work relates to the literature on industry and peer effects in asset pricing, including industry momentum (Moskowitz and Grinblatt, 1999), industry lead-lag (Hou, 2007), and industry adjustments (Goodman and Peavy, 1983). Many of these effects attenuate in recent samples or fail to clear the modern $t \approx 3$ hurdle (Harvey et al., 2016), especially in multivariate settings, as urged by Cochrane (2011). In Green et al. (2017), none of nine industry-related characteristics remains significant once all characteristics enter jointly and microcaps are properly treated. In contrast, our comprehensive index — using peer information from two angles — clears both recent-sample and full-sample thresholds, highlighting the central role of peer-based information in detecting mispricing. We also contribute to the broader cross-firm predictability literature that studies peers' past returns (Cohen and Frazzini, 2008; Cohen and Lou, 2012; Hoberg and Phillips, 2018; Lee et al., 2019; Parsons et al., 2020; Ali and Hirshleifer, 2020) and fundamentals such as earnings surprises (Müller, 2019), as well as recent work that models cross-asset signal interactions (Kelly et al., 2023, 2025; Avramov and He, 2025), and to deviation-based and pairs-trading approaches (Hameed and Mian, 2015; Gatev et al., 2006). Our innovation is to *systematically* integrate peer attributes so as to position both the peer groups among competitors and the firm within its peer group, and to show that the resulting predictor remains significant even after controlling for well-documented cross-firm effects.

The paper proceeds as follows. Section 2 presents the data, documents preliminary evidence on dual peer effects and cross-predictability, and details the construction of PI and its relation to recent cross-predictability strategies. Section 3 reports the core empirical findings, including cross-sectional regressions, portfolio analysis, and spanning tests. Section 4 discusses the economic forces underlying PI. Section 5 examines asymmetric peer networks. Section 6 concludes.

2. Methodology and data

2.1. Data description

We construct a monthly panel by merging CRSP, Compustat (annual and quarterly), and IBES. CRSP provides returns (including delisting returns), prices, shares outstanding, exchange codes, and share codes; Compustat supplies financial statement variables; and IBES contributes analyst coverage and earnings estimates. We obtain common risk factors and the risk-free rate from Kenneth R. French's data library.²

Our characteristic universe starts from the comprehensive sample compiled by Jensen et al. (2023), spanning January 1980–December 2024.³ The stock universe includes all U.S. common shares on NYSE/AMEX/NASDAQ (CRSP share codes 10 or 11). We exclude “nano” stocks with market capitalization below the 1st percentile of NYSE market cap in each month.

The raw set contains 153 stock-level characteristics. Following Didisheim et al. (2024) and Kelly et al. (2025), we restrict to 130 characteristics with fewer than 30% missing observations over the full sample. Consistent with Gu et al. (2020), in each month we cross-sectionally rank-standardize each characteristic and map it to $[-0.5, 0.5]$; missing values are replaced with the cross-sectional median (zero). Characteristics are grouped into 13 categories: *Accruals*, *Debt*

² We thank Kenneth French for making the data available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

³ Open-source dataset at WRDS: <https://wrds-www.wharton.upenn.edu/pages/get-data/contributed-data-forms/global-factor-data/>.

Issuance, Investment, Low Leverage, Low Risk, Momentum, Profit Growth, Profitability, Quality, Seasonality, Short-Term Reversal, Size, and Value. Precise definitions, formulas, source fields, and category assignments are listed in Table 12 (Appendix).

2.2. Dual peer effects and cross-stock predictability

Classic return prediction links a firm's own characteristics to its future returns via

$$r_{i,t+1} = h(\mathbf{x}_{i,t}) + \epsilon_{i,t+1}. \quad (1)$$

Here, $r_{i,t+1}$ is the return on stock i from t to $t+1$; $\mathbf{x}_{i,t} = (x_{1,i,t}, \dots, x_{S,i,t})'$ is an S -dimensional vector of firm i 's characteristics observed at time t , with $x_{s,i,t}$ denoting characteristic s ; $h(\cdot)$ is a function mapping characteristics into expected returns; and $\epsilon_{i,t+1}$ is an idiosyncratic prediction error with $\mathbb{E}[\epsilon_{i,t+1} | \mathbf{x}_{i,t}] = 0$.

Such a firm-specific focus can miss *cross-predictability* conveyed by economically linked peers. To illustrate, consider a single characteristic s and a linear model,

$$r_{i,t+1} = x_{s,i,t} \beta + \epsilon_{i,t+1}. \quad (2)$$

For any defined peer set g_i (the set of peers of firm i , excluding i itself), decompose $x_{s,i,t}$ into a *leave-one-out peer average* and a *within-peer deviation*:

$$z_{s,i,t} \equiv \frac{1}{|g_i|} \sum_{j \in g_i} x_{s,j,t}, \quad \tilde{x}_{s,i,t} \equiv x_{s,i,t} - z_{s,i,t}, \quad (3)$$

where $|g_i|$ denotes the number of firms in the peer group g_i .

Substituting this decomposition into the regression yields

$$r_{i,t+1} = z_{s,i,t} \beta + \tilde{x}_{s,i,t} \beta + \epsilon_{i,t+1}. \quad (4)$$

Eq. (4) by itself does not imply peer-based predictability; it shows that the standard firm-own regression *restricts* the coefficients on the peer-average and deviation components to be equal. If peers are economically meaningful (e.g., industry, supply-chain, shared analysts), the two components may enter with different slopes—what we term *dual effects*.

Whether the slope coefficients are indeed identical is an empirical question. We test this restriction using 2-digit SIC industry peers and extend Eq. (4) to a multiple-characteristic setting:

$$r_{i,t+1} = \mathbf{z}'_{i,t} \boldsymbol{\beta}_z + \tilde{\mathbf{x}}'_{i,t} \boldsymbol{\beta}_{\tilde{x}} + \epsilon_{i,t+1}, \quad (5)$$

where $\mathbf{z}_{i,t} = (z_{1,i,t}, \dots, z_{S,i,t})'$ and $\tilde{\mathbf{x}}_{i,t} = (\tilde{x}_{1,i,t}, \dots, \tilde{x}_{S,i,t})'$ are S -dimensional vectors collecting peer averages and within-peer deviations of all characteristics, and $\boldsymbol{\beta}_z = (\beta_{z,1}, \dots, \beta_{z,S})'$ and $\boldsymbol{\beta}_{\tilde{x}} = (\beta_{\tilde{x},1}, \dots, \beta_{\tilde{x},S})'$ are the corresponding slope vectors.

We conduct an F -test of $H_0: \boldsymbol{\beta}_z = \boldsymbol{\beta}_{\tilde{x}}$ for the comprehensive set of $S = 130$ characteristics. The resulting statistic is $F = 29.91$, rejecting H_0 at the 1% level. Repeating this test within each of the 13 characteristic groups (Accruals, Debt Issuance, Investment, Low Leverage, Low Risk, Momentum, Profit Growth, Profitability, Quality, Seasonality, Short-Term Reversal, Size, and Value) yields F -statistics ranging from 7.75 to 270.70, again strongly rejecting equality in every group.

These results indicate that decomposing characteristics into peer averages and within-peer deviations uncovers systematic cross-stock structure beyond firm-own signals. To address high dimensionality and stabilize estimation, we construct the *Peer Index (PI)* using ridge regressions that load on both peer averages and deviations.

2.3. PI formation

We consider $S = 130$ predictive characteristics. For each characteristic s , we calculate the industry peer-group average $z_{s,i,t}$ and the within-peer deviation $\tilde{x}_{s,i,t}$ for all stock-month observations based on

2-digit SIC industry peers. Next, we relate these (standardized) peer-average characteristics and deviations to future returns through ridge regressions.

In our baseline design, the Peer Index (PI) is constructed monthly using an expanding-window scheme. In month t , we estimate a pooled panel ridge regression of stock returns on all lagged peer-average characteristics and lagged deviations.⁴

We adopt ridge regression, as prior work documents ridge's effectiveness in exploiting many weak signals (see, e.g., Kelly et al. (2024) and Shen and Xiu (2025)). The optimal penalty parameter is selected each month using 3-fold cross-validation.

The resulting slope coefficients capture both time-series and cross-sectional return predictability. Given these estimates, the Peer Index (PI) for month t is computed as the one-step-ahead, out-of-sample predicted return based on the peer-average characteristics and deviations realized at month t .

This method of forecasting returns was previously referred to as the “projected return” by Haugen and Baker (1996) and the “fundamental implied return” (FIR) by Huang et al. (2019). It ensures that no look-ahead bias is present and that real-time predictions optimally combine available information. By aggregating a wide range of peer-average variables and deviations from peer averages into the Peer Index (PI), we substantially reduce the dimensionality of predictive coefficients, transforming potential cross-predictability into a more interpretable and parsimonious index.

Descriptive statistics for the firm characteristics and the Peer Index (PI) are presented in Table 13 in the Appendix. The correlations between the PI and individual characteristics are generally modest, with the highest absolute correlation being 0.217 with the performance mispricing factor (*mispricing_perf*). Additionally, the PI does not exhibit particularly large correlations with any specific category of variables. These results suggest that the newly proposed peer-based index contains information that is markedly different from individual components.

We present descriptive statistics for the variables used to construct the Peer Index (PI) in the ridge regressions, as detailed in Table 14 in the Appendix. The variables are ranked by the magnitude of their average coefficients across all estimation windows. For each variable, we report its name (`_peer` and `_dev` denote peer average and deviation, respectively) and the mean coefficient across windows, which reflects the variable's importance in constructing the PI.

Several variables in the “Low Risk” category have large coefficients, including the number of zero trades across different horizons (*zero_trades_21d*, *zero_trades_126d*, etc.). Notably, momentum-type variables play an important role. For example, the peer-average past 1-month return (*ret_1_0*) is a prominent predictor, consistent with the industry momentum. Other past return/price variables, including the 12-month return (*ret_12_1*) and the ratio of current price to the 1-year high (*prc_highprc_252d*), also have large coefficients. “Quality”, “Value”, and “Profitability” related signals — such as the performance mispricing factor (*mispricing_perf*), sales-to-market (*sale_me*), assets-to-market (*at_me*), book-to-market (*bm_me*), operating profits to lagged book assets (*op_atl1*), and quarterly return on equity (*niq_be*) — are also important determinants of the index.

⁴ Our baseline expanding-window design reflects the view that, in the presence of weak signals and high noise, aggregating as much historical data as possible can improve signal estimation and reduce overfitting. However, this approach assumes a relatively stable data-generating process and may underperform when predictability patterns shift over time. To assess sensitivity to this choice, we also implement rolling-window versions of our main predictive procedures. Specifically, following Kelly et al. (2024) and Didisheim et al. (2024), we re-estimate models using fixed-length windows of 12, 60, 120, and 360 months.

Furthermore, we find that the signs of the variables' ridge coefficients generally align with those of their original firm-specific counterparts (before transformation into peer averages and deviations) in the Fama–MacBeth regressions.⁵ This consistency suggests that stocks with high PI values tend to belong to stronger industry peer groups and exhibit superior traits relative to their peers. Consequently, they are more likely to experience higher unexpected returns in the future.

These findings provide preliminary evidence that the PI uniquely captures both the overall strength of an industry and a firm's relative standing within it. Additional supporting evidence is presented later in the text.

2.4. Relation to principal portfolios

Our Peer Index (PI) is closely related to the cross-stock predictability framework of Kelly et al. (2023) (PP). In PP, return-predictive information is organized through a position matrix $L \in \mathbb{R}^{N \times N}$ that loads each stock not only on its own characteristics but also on those of other firms. The matrix L is typically estimated flexibly from the data and is therefore largely unrestricted.

In our setting, we instead *pre-specify* the position matrix using observable economic relations. In the baseline specification, we use an industry-based linkage matrix $L^{\text{ind}} \in \mathbb{R}^{N \times N}$ defined by

$$(L^{\text{ind}})_{ij} = \mathbf{1}\{i \text{ and } j \text{ are in the same industry}\} \times (1/|g_i|), \quad (6)$$

so that the channel through which cross-firm information enters is transparent and economically interpretable. More generally, any network — industries, customer–supplier links, shared-analyst coverage — can be encoded by an appropriate choice of L .

Given a generic position matrix L , we generalize the earlier decomposition in Eq. (3) as

$$z_{s,i,t} \equiv \mathbf{x}'_{s,t} L_i, \quad \tilde{x}_{s,i,t} \equiv x_{s,i,t} - z_{s,i,t}, \quad (7)$$

where $\mathbf{x}_{s,t} = (x_{s,1,t}, \dots, x_{s,N,t})' \in \mathbb{R}^N$ is the cross-section of characteristic s at time t , and L_i denotes the i th row of L , written as a column vector. The term $z_{s,i,t}$ aggregates peers' characteristics according to L , and $\tilde{x}_{s,i,t}$ measures stock i 's deviation from this peer benchmark. This formulation covers both unweighted networks (such as industries) and weighted ones (such as customer–supplier networks).⁶

For a given characteristic s and position matrix L , the PP portfolio based on Kelly et al. (2023) assigns to stock i a weight proportional to $\mathbf{x}'_{s,t} L_i$. Under our industry network, this becomes $w_{s,i,t}^{PP} \propto \mathbf{x}'_{s,t} L_i^{\text{ind}} = z_{s,i,t}$. Thus, with $L = L^{\text{ind}}$, the PP signal coincides exactly with our industry peer-average characteristic. The peer-average leg of PI is therefore a *structurally restricted, economically identified* instance of the PP operator.

PI goes further by allowing returns to load not only on peer averages $z_{s,i,t}$ but also on the within-peer deviations $\tilde{x}_{s,i,t}$ in Eq. (7). For a given L , PP effectively prices the peer-aggregated signal associated with each characteristic. Our specification relaxes this restriction by letting the data assign separate coefficients to $z_{s,i,t}$ and $\tilde{x}_{s,i,t}$. In economic terms, PI combines information about the overall strength of a firm's peer group with information about the firm's relative position within that group. This additional deviation channel is what allows PI to extract cross-sectional contrast within economically homogeneous peer networks, beyond what a single PP-style operator can capture.

Kelly et al. (2023) show that linear portfolio operators admit a symmetric–antisymmetric decomposition, where the symmetric part

behaves like a factor exposure and the antisymmetric part captures “pure alpha”. Our baseline industry matrix L^{ind} is symmetric by construction, so the antisymmetric PP channel is mechanically absent in that case.⁷ In Section 5.2, we return to the symmetric–antisymmetric decomposition for asymmetric networks — shared-analyst coverage and customer–supplier links — where antisymmetry in L becomes an additional source of predictability.

2.5. Relation to Artificial Intelligence Pricing Models (AIPM)

Our Peer Index (PI) is also related to the Artificial Intelligence Asset Pricing Models (AIPM) recently proposed by Kelly et al. (2025). In AIPM, the key object is a characteristic-based attention matrix $A \in \mathbb{R}^{N \times N}$ that governs cross-asset information flow.⁸ Let X_t be the $N \times S$ matrix of characteristics at time t , whose i th row is $\mathbf{x}'_{i,t}$. The linear portfolio transformer in AIPM assigns weight to asset i at time t as

$$w_{i,t}^{\text{AIPM}} = \lambda' X'_i A_i, \quad (8)$$

where A_i is the i th row of A written as a column vector, and λ is the $S \times 1$ vector of characteristic weights.

The attention matrix A is a cross-predictability matrix: a typical entry A_{ij} measures the strength of information flow from asset j to asset i . Given this interpretation, A can naturally be used as a position matrix in our framework. Setting $L = A$ and applying the weighted peer-average construction in Eq. (7) yields, for each characteristic s ,

$$z_{s,i,t} \equiv \sum_j A_{ij} x_{s,j,t} = A'_i \mathbf{x}_{s,t}, \quad \text{and hence} \quad z_{i,t} = X'_i A_i. \quad (9)$$

If we further set $\lambda = \beta_z$, equal to the slope vector on the peer-average variables in our PI regression, then the AIPM portfolio is directly comparable to the peer-average component of PI:

$$w_{i,t}^{\text{AIPM}} = \lambda' X'_i A_i = \beta'_z z_{i,t}. \quad (10)$$

In this sense, our industry-based specification corresponds to an AIPM in which the attention matrix is restricted to a transparent, economically motivated network.

Recognizing that peers — and hence the position/attention matrix — can be specified in many ways (including via the flexible attention structure in AIPM), a natural next step is to let the data adjust an economically grounded baseline. One convenient way to do so is through Bayesian shrinkage. Starting from the industry-based linkage matrix L^{ind} , we can place an informative prior on the attention matrix A centered at L^{ind} :

$$A_{ij} \sim \mathcal{N}((L^{\text{ind}})_{ij}, \tau^2). \quad (11)$$

This prior treats L^{ind} as the default peer structure and allows the data to tilt the attention matrix away from pure industry links where warranted.

More generally, one could combine the structural PI decomposition (peer averages and within-peer deviations) with the flexible attention mechanisms of AIPM. For example, spike-and-slab or hierarchical priors on A_{ij} could be used to quantify which links are tightly anchored to economically defined peers and which links emerge endogenously from the data. We leave such Bayesian implementations of PI-type structures within the AIPM framework to future research.

⁵ The online appendix of Jensen et al. (2023) provides the signs of their characteristics. A positive (negative) coefficient indicates that a higher value of the characteristic is associated with higher (lower) returns. We then examine whether the sign of a peer-average or deviation variable matches that of its original counterpart in the FM regression.

⁶ The matrix L here is the transpose of the position matrix in Kelly et al. (2023).

⁷ Our baseline SIC-based L^{ind} is symmetric. One can extend the industry matrix to an asymmetric one — for example, by using the method of Yan and Yu (2023) to extract data-driven cross-stock industry linkages — and then conduct the decomposition analysis for the asymmetric industry network. In this paper, we focus on pre-specified economic networks that do not require estimation, and we leave this extension to future work.

⁸ In Kelly et al. (2025), the attention matrix is naturally dynamic, denoted A_t . For notational simplicity, we suppress the time subscript and write it as static.

3. Core empirical findings

This section presents the core empirical findings on the predictive performance of PI.

3.1. Cross-sectional regressions

We examine the predictive content of the Peer Index (PI) for future returns using a series of value-weighted cross-sectional regressions in the spirit of [Fama and MacBeth \(1973\)](#). For interpretability, we rank each month's PI cross-sectionally and linearly map it to the interval $[-0.5, 0.5]$, which makes its coefficient comparable to those of other (already standardized) characteristics. The main results appear in [Table 1](#).

In Panel A, the dependent variable is the one-month-ahead return. To test whether PI merely proxies for well-known past-price effects at the stock or industry level, we estimate specifications that add two standard controls — short-term reversal (MOM1) and momentum (MOM12) — and we further include industry effects via either industry momentum (INDMOM) or the industry lead-lag signal of [Hong et al. \(2007\)](#). The latter uses the average past returns of the largest 30% of firms in an industry, capturing within-industry information diffusion from large to small firms. Without PI, the reversal, momentum, and industry variables are strongly significant in the cross-section. Once PI is included, the coefficients on short-term reversal, momentum, industry momentum, and the lead-lag signal become largely insignificant at conventional levels. These patterns indicate that PI subsumes both industry-level and firm-level return-predictive components that these controls were capturing. PI itself remains highly significant in value-weighted Fama–MacBeth regressions, with t -statistics around six—exceeding common thresholds for economic relevance (e.g., [Harvey et al. \(2016\)](#)).

A natural question is whether flexible machine-learning methods that rely solely on firms' own characteristics can replicate the predictive power of PI. Our peer-based measure integrates information from economically related firms, so we need to rule out the possibility that PI is simply a nonlinear re-packaging of already known firm-level signals. To do so, we follow [Gu et al. \(2020\)](#) and construct three benchmark ML forecasts — gradient-boosted regression trees (GBRT), random forests (RF), and neural networks (NN) — and include these forecasts as additional controls in the Fama–MacBeth regressions. We adopt the training design and hyperparameter choices in [Gu et al. \(2020\)](#). For GBRT, we tune the maximum depth (L), shrinkage factor (ν), and number of trees (B); for RF, we tune the maximum depth (L) and number of bootstrap samples (B); and for NN we use a three-layer architecture with 32, 16, and 8 neurons, respectively.⁹ All models are trained in an expanding scheme: 1973–1977 (60 months) for initial training, 1978–1979 (24 months) for validation, and out-of-sample evaluation starting in January 1980; the models are refit annually, as in [Gu et al. \(2020\)](#).

The results, reported in Panel B, show that PI's slope remains economically large and statistically significant even after controlling for these flexible ML forecasts, with t -statistics of 4.29 (GBRT), 4.17 (RF), and 3.15 (NN). Put differently, allowing the data to learn rich nonlinear transformations of firm-only characteristics does *not* wash out the incremental content of peer-based information. This pattern is consistent with the view that PI contributes information that is cross-stock in nature, rather than information that can be engineered from a single firm's characteristics. Consistent with this interpretation, our other exercises (reported later in the text) — out-of-sample forecasting

of returns and earnings surprises, as well as portfolio sorts that also condition on ML predictions — show that PI continues to add explanatory power. Taken together, the evidence indicates that applying modern ML to firm-level predictors is not enough to recover the peer-linked information that PI is designed to capture.

We next assess the robustness of these cross-sectional findings. *First*, we expand the set of controls to include all 130 characteristics. As expected, the magnitude of the PI coefficient declines once we saturate the regression with a broad universe of firm-level signals, but PI remains highly significant, confirming that its predictive content is not an artifact of an omitted characteristic. *Second*, [Fama and French \(2008\)](#) show that stocks with market capitalization below the NYSE 20th percentile account for 60% of all stocks but only about 3% of aggregate market capitalization; microcaps feature the largest cross-sectional dispersions and can inflate anomaly magnitudes if not addressed. In our main analysis, we already exclude “nano” stocks (below the NYSE 1st percentile). As a robustness check, we also exclude all microcaps (below the NYSE 20th percentile), reducing the sample from 2,088,332 to 1,043,044 firm-months. Even in this “all-but-microcaps” sample, the PI slope remains highly significant with a t -ratio around five.

Third, prior work documents attenuation of many anomalies in recent years (e.g., [Chordia et al. \(2014\)](#) and [Green et al. \(2017\)](#)). Using 2003 as a breakpoint and restricting to post-2003 data, PI remains statistically and economically significant — with t -statistics exceeding seven — whereas many other characteristics exhibit a sharp decline in return predictability, consistent with the extant literature. *Fourth*, our baseline expanding-window design pools as much historical data as possible to stabilize weak-signal estimation in noisy environments. Recognizing potential nonstationarity, we also implement rolling windows following [Kelly et al. \(2024\)](#) and [Didisheim et al. \(2024\)](#) with fixed lengths of 12, 60, 120, and 360 months. Panel C shows that the PI effect is robust across window choices. While the full-sample PI coefficient rises with window length, the post-2003 coefficient is non-monotonic, reaching its maximum with a 360-month window—suggesting that shifts in the data-generating process can make post-2003 performance sensitive to the inclusion of older data.

Fifth, we examine longer-horizon predictability by cumulating returns up to three years. Panel D shows that the PI coefficient remains positive and statistically significant across horizons, with no evidence of reversal within the three-year window. This persistence makes it difficult to attribute the results to investor overreaction. *Sixth*, mounting evidence suggests stronger return predictability in high-volatility ([Wang and Xu, 2015](#)), high-friction/limited-arbitrage ([Avramov et al., 2023](#)), and high-sentiment ([Stambaugh et al., 2012](#)) states. We therefore estimate cross-sectional regressions separately in high and low volatility, liquidity, and sentiment regimes. Volatility is measured by the VIX, illiquidity by [Amihud \(2002\)](#), and sentiment by [Baker and Wurgler \(2006\)](#). Panel E shows that the PI effect remains significant across these market states.

Finally, because our baseline PI is deliberately simple and linear in peer averages and peer deviations, we ask whether adding nonlinear structure materially improves predictive power. We therefore build two enlarged signal sets. Under the *Feature-first* transformation, for each of the 130 original characteristics, we first take quadratic and cubic terms and then form peer-average and peer-deviation variables, yielding $130 \times 2 \times 3 = 780$ peer-based signals. Under the *Peer-first* transformation, we first construct $130 \times 2 = 260$ peer-average and peer-deviation variables and then take quadratic and cubic terms, again totaling 780 signals. Using either augmented set, we estimate a nonlinear Peer Index, $PI_{\text{nonlinear}}$, via ridge regression and re-run the Fama–MacBeth cross-sectional regressions. As reported in Panel F, $PI_{\text{nonlinear}}$ is strongly significant and — crucially — remains incrementally significant when the original linear PI is included. This finding shows that the economic structure captured by PI can be usefully enriched with modest nonlinear complexity, but that the linear PI already captures the core cross-stock signal.

⁹ In Table 1 of [Gu et al. \(2020\)](#), the three-layer NN outperforms alternatives in terms of out-of-sample R^2 . We likewise find NN3 performs best in our data and, for brevity, focus on NN3.

Table 1
Value-weighted Fama–MacBeth cross-sectional regressions.

Panel A: Basic controls						
Dependent variable	Observations	PI	MOM1	MOM12	INDMOM	Lead-lag
R_{t+1}	2,088,332		−0.68*** (−3.19)	0.83** (2.19)	0.51*** (3.15)	
R_{t+1}	2,088,332	0.99*** (5.90)	−0.24 (−1.15)	0.54 (1.44)	0.06 (0.36)	
R_{t+1}	2,088,332		−0.78*** (−3.78)	0.86** (2.26)		0.60*** (3.56)
R_{t+1}	2,088,332	0.85*** (5.71)	−0.41** (−2.00)	0.60 (1.60)		0.33* (1.80)
Panel B: Robustness						
Dependent variable	Observations	PI				
R_{t+1}	With ML control (GBRT)	2,088,332	0.81*** (4.29)			
R_{t+1}	With ML control (RF)	2,088,332	0.78*** (4.17)			
R_{t+1}	With ML control (NN)	2,088,332	0.61*** (3.15)			
R_{t+1}	With all controls	2,088,332	0.50*** (3.87)			
R_{t+1}	Remove microcaps	1,043,044	0.92*** (4.61)			
R_{t+1}	Post 2003 Sample	942,090	1.96*** (7.47)			
Panel C: Window settings						
Dependent variable	Window size	Observations	PI	PI post 2003		
R_{t+1}	Rolling 12	2,088,332 (942,090)	2.57*** (8.66)	1.46*** (5.85)		
R_{t+1}	Rolling 60	2,088,332 (942,090)	2.81*** (9.64)	1.35*** (5.72)		
R_{t+1}	Rolling 120	2,088,332 (942,090)	3.00*** (10.51)	1.57*** (6.69)		
R_{t+1}	Rolling 360	2,088,332 (942,090)	3.26*** (11.60)	1.96*** (7.31)		
R_{t+1}	Expanding	2,088,332 (942,090)	3.28*** (11.52)	1.96*** (7.47)		
Panel D: Long-term predictability						
Dependent variable	Observations	PI				
$R_{t+1:t+6}$	2,088,332	2.43*** (2.62)				
$R_{t+1:t+12}$	2,088,332	3.61** (2.19)				
$R_{t+1:t+36}$	2,088,332	8.16*** (2.57)				
Panel E: Market state						
Dependent variable		Observations high state	PI high state	Observations low state	PI low state	
R_{t+1}	Volatility	863,531	1.07*** (2.80)	779,723	0.93*** (3.94)	
R_{t+1}	Liquidity	1,027,966	1.04*** (4.07)	1,097,253	0.96*** (2.95)	
R_{t+1}	Sentiment	1,046,014	1.39*** (5.35)	969,629	0.75** (2.48)	
Panel F: Nonlinear effect						
Dependent variable		Observations	PI nonlinear	PI		
R_{t+1}	Feature-first transformation	2,088,332	0.75*** (4.51)			
R_{t+1}	Feature-first transformation	2,088,332	0.49*** (2.90)	0.88*** (4.40)		
R_{t+1}	Peer-first transformation	2,088,332	1.08*** (5.99)			
R_{t+1}	Peer-first transformation	2,088,332	0.64*** (2.93)	0.59** (2.40)		

Panels A–F report average slopes and Newey–West t -statistics (12 lags) from monthly value-weighted Fama–MacBeth regressions. Monthly returns are expressed in percent. MOM1 and MOM12 follow Jegadeesh (1990) and Jegadeesh and Titman (1993). INDMOM is the industry momentum variable from Moskowitz and Grinblatt (1999). Lead–Lag is the industry lead–lag signal from Hong et al. (2007). Panel E examines the PI's predictability across market states; “low” (“high”) states are months below (above) the cross-sectional median of the previous month's value of the state variable (VIX for volatility, Amihud (2002) for illiquidity, and Baker and Wurgler (2006) for sentiment). Panel F evaluates a nonlinear version of PI constructed from quadratic and cubic transformations of peer-average and peer-deviation characteristics. The sample period is January 1980–December 2024. In the main sample, we exclude “nano” stocks (market equity below the NYSE 1st percentile). The “no microcaps” sample excludes firms below the NYSE 20th percentile of market equity. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2
Monthly out-of-sample performance.

	NN	GBRT	RF
$R^2_{OOS}^{ML}$	0.322%	0.242%	0.306%
$R^2_{OOS}^{PI}$	0.325%	0.325%	0.325%
$R^2_{OOS}^{AVE}$	0.498%	0.391%	0.427%
DM	2.387	2.153	1.740
p-value	(0.017)	(0.031)	(0.082)

This table reports out-of-sample performance for three machine-learning methods: neural network (NN), gradient-boosted regression trees (GBRT), and random forest (RF). For each method, we report R^2_{OOS} for: (1) a benchmark using 130 firm-specific characteristics (*ML*); (2) a model using only the Peer Index (*PI*); and (3) a simple average of the *ML* and *PI* forecasts (*AVE*). The ML models use an expanding-window scheme with an initial 60-month training period (1973–1977) and a 24-month validation period (1978–1979), with the out-of-sample period starting in January 1980. The *PI* model is estimated with a rolling 84-month window, yielding an out-of-sample start of January 1987. “DM” reports the modified Diebold–Mariano statistic (Gu et al., 2020 adjustment) comparing *AVE* vs. *ML*; Newey–West standard errors are used and *p*-values appear in parentheses.

3.2. Out-of-sample R^2

We evaluate the predictive power of PI through out-of-sample forecasting accuracy. For each of the three machine-learning methods considered earlier, we compute the out-of-sample R^2 for three models: (1) a benchmark model that includes only the 130 firm-specific characteristics, (2) a model that uses only PI as a predictor, and (3) a simple averaging model that takes the mean of the machine-learning benchmark predictor and the PI-based predictor.

As in the cross-sectional analyses, the initial training window spans 1973–1977 (60 months), followed by a validation window covering 1978–1979 (24 months). The first out-of-sample period begins in January 1980. We adopt an expanding-window approach: each year the training sample expands by one year and the model is re-estimated, with the validation sample rolling forward accordingly. For the PI-based model, we use a rolling estimation scheme with 84 months — the same length as the combined initial training and validation window of the ML models — so that the first out-of-sample period for PI begins in January 1987.

The out-of-sample R^2 is calculated as:

$$R^2_{OOS} = 1 - \frac{\sum_{i,t \in I_{\text{test}}} (r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{i,t \in I_{\text{test}}} r_{i,t+1}^2}, \quad (12)$$

where I_{test} denotes the testing sample.

To evaluate differences in out-of-sample prediction errors among models, we employ the Diebold and Mariano (2002) test. Specifically,

following the modification in Gu et al. (2020), we first average each model’s prediction errors cross-sectionally and then run the DM test on the resulting time series. Let

$$d_{t+1} = \frac{1}{n_{\text{test},t+1}} \sum_{i=1}^{n_{\text{test},t+1}} \left[(\hat{e}_{i,t+1}^{\text{model1}})^2 - (\hat{e}_{i,t+1}^{\text{model2}})^2 \right], \quad (13)$$

where $\hat{e}_{i,t+1}^{\text{model}}$ is the one-step-ahead prediction error for stock i at time t from the indicated model, and $n_{\text{test},t+1}$ is the number of stocks in the testing cross-section. Denoting by $\bar{d}$ the sample mean of $\{d_t\}$ and by $\hat{\sigma}_{\bar{d}}$ its Newey–West standard error, the DM statistic is $DM = \bar{d}/\hat{\sigma}_{\bar{d}}$. To assess whether PI provides incremental information, we compare (i) the PI-only model and (ii) the simple averaging model against the machine-learning benchmark that relies solely on firm-specific characteristics.

We report the pairwise comparison results in Table 2. The neural network (NN), gradient-boosted regression trees (GBRT), and random forest (RF) benchmarks achieve out-of-sample R^2 values of 0.322%, 0.242%, and 0.306%, respectively. In comparison, the PI-only model attains $R^2_{OOS} = 0.325\%$, which is higher than all three ML benchmarks. The corresponding gains are small versus NN (+0.003 percentage points), modest versus RF (+0.019 percentage points), and more pronounced versus GBRT (+0.083 percentage points).

The DM test formally compares the averaged (PI+ML) forecast to the standalone ML forecast. The null is equal predictive accuracy. The test statistics indicate significance at the 5% level for NN and GBRT and at the 10% level for RF. In unreported checks, the averaging model not only improves R^2_{OOS} relative to the ML benchmarks but also reduces the volatility of forecast errors.

Taken together, incorporating the Peer Index provides valuable information for enhancing out-of-sample prediction accuracy. Even flexible nonlinear models trained solely on firm-specific characteristics do not fully capture the predictive content embedded in peer relationships. Leveraging economically motivated cross-predictability thus delivers measurable improvements in forecasting performance.

3.3. Portfolio analysis

We examine the predictive content of the Peer Index (PI) through monthly portfolio sorts. At each month-end, stocks are ranked by PI into five portfolios, and we compute next-month equal- and value-weighted returns; portfolios are rebalanced monthly.

To isolate the component of PI that is not already spanned by flexible nonlinear models based on firm-level characteristics, we regress the PI signal on expected-return proxies generated by a neural network trained on 130 firm characteristics. We then remove the portion

Table 3
Risks and alphas of PI-based portfolios.

	Excess ret	Alpha	Market	SMB	HML	RMW	CMA	UMD	REV
Panel (A) Equal-weighted PI portfolios (7-factor model)									
Top-minus-bottom	3.33*** (23.03)	3.18*** (23.60)	0.03 (1.01)	0.10** (2.15)	0.06 (1.01)	−0.14** (−2.25)	0.38*** (4.30)	0.25*** (7.75)	−0.18*** (−4.34)
Top-minus-bottom (post 2003)	2.25*** (13.44)	2.24*** (13.81)	−0.05 (−1.17)	0.02 (0.34)	0.09 (1.21)	0.16* (1.80)	0.39*** (3.60)	0.07* (1.70)	−0.06 (−0.98)
Top-minus-bottom (adjust ML)	1.87*** (12.94)	1.79*** (14.00)	0.10*** (3.26)	−0.03 (−0.63)	0.17*** (3.01)	−0.11* (−1.88)	0.25*** (2.98)	0.18*** (6.03)	−0.41*** (−10.43)
Panel (B) Value-weighted PI portfolios (7-factor model)									
Top-minus-bottom	0.89*** (6.05)	0.68*** (5.45)	0.07** (2.47)	−0.08* (−1.78)	0.21*** (3.88)	−0.20*** (−3.59)	0.20** (2.43)	0.41*** (14.25)	−0.18*** (−4.58)
Top-minus-bottom (post 2003)	0.34* (1.73)	0.34** (2.12)	−0.02 (−0.40)	−0.17** (−2.39)	0.30*** (4.20)	0.04 (0.41)	0.30*** (2.81)	0.36*** (8.78)	−0.01 (−0.18)
Top-minus-bottom (adjust ML)	0.53*** (3.76)	0.40*** (3.11)	0.09*** (3.00)	−0.16*** (−3.53)	0.22*** (3.86)	−0.11* (−1.85)	0.14* (1.62)	0.24*** (8.12)	−0.26*** (−6.63)

This table reports the monthly excess returns, factor loadings, and alphas of PI-based portfolios, considering a seven-factor model includes the Fama–French five factors plus the momentum factor and the reversal factor. Panel A and B show the results for the equal-weighted and value-weighted portfolios, respectively. The sample period is Jan 1980–Dec 2024. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

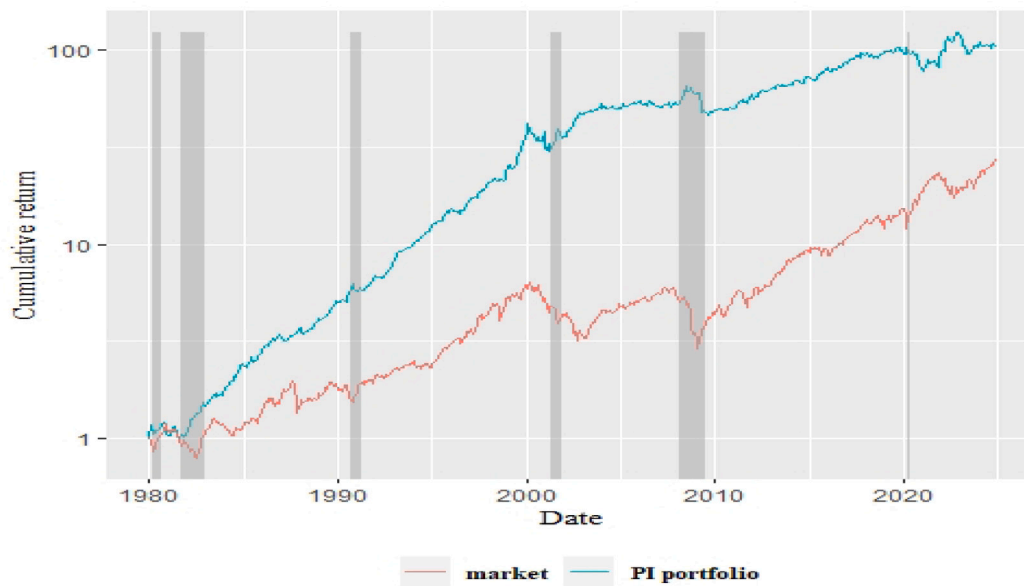


Fig. 1. PI-based portfolio. This figure plots the value of portfolios over time after investing \$1 at the beginning of the sample period. The PI portfolio represents the value-weighted top-minus bottom PI-based portfolio. The market is the CRSP value-weighted index. The sample period is Jan 1980 to Dec 2024. Shaded areas show the periods of recessions from Federal Reserve Economic Data (FRED). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

explained by this benchmark and retain the intercept plus residual as a purified PI signal, which we use to form a monthly rebalanced long-short portfolio.

Table 3 reports average excess returns, alphas, and factor loadings for these portfolios based on a seven-factor model that augments the Fama–French five factors (Fama and French, 2015) with the momentum factor (Carhart, 1997) and the short-term reversal factor (Jegadeesh, 1990).

Panel A reports results for an equal-weighted top-minus-bottom (T–B) hedge portfolio, its post-2003 subsample, and an ML-adjusted version. The T–B portfolio has a small, statistically insignificant market loading; a positive SMB loading; and a small, insignificant HML loading. It loads negatively on profitability (RMW). Importantly, despite this negative RMW exposure, we later show that PI positively predicts subsequent earnings surprises, indicating that PI embeds forward-looking information not captured by contemporaneous profitability. The portfolio loads significantly and positively on CMA, consistent with investment-style differences between high- and low-PI firms (the former investing more conservatively, the latter more aggressively), which helps rationalize the return spread. It also exhibits a significant positive momentum (UMD) loading and a significant negative short-term reversal (REV) loading, implying that high-PI stocks are recent winners and low-PI stocks recent losers. These patterns are similar post-2003 and remain after ML adjustment.

Nonetheless, the seven-factor alpha is large and precisely estimated: 3.18% per month ($t = 23.60$). The post-2003 alpha declines but remains substantial at 2.24% ($t = 13.81$). After orthogonalizing PI to the ML benchmark, the long-short portfolio's excess return falls from 3.33% ($t = 23.03$) to 1.87% ($t = 12.94$), yet the seven-factor alpha remains both economically and statistically significant at 1.79% ($t = 14.00$).

Panel B reports the value-weighted results. As expected with cap-weighting, magnitudes attenuate but stay meaningful: the baseline long-short portfolio earns 0.89% per month ($t = 6.05$) with a seven-factor alpha of 0.68% ($t = 5.45$). Robustness carries through: the post-2003 value-weighted alpha is 0.34% ($t = 2.12$), and the ML-adjusted long-short portfolio delivers 0.40% ($t = 3.11$), showing that PI's performance survives both the recent subsample and the ML adjustment.

Table 4

Annual alphas of PI-portfolios over longer holding periods.

	Holding period		
	3	6	12
VW top quintile	0.36 (0.49)	0.85 (1.49)	0.79* (1.73)
VW bottom quintile	−4.01*** (−4.84)	−2.47*** (−3.68)	−1.44*** (−2.82)
VW spread portfolios	4.37*** (7.46)	3.31*** (8.77)	2.23*** (8.67)
VW spread portfolios (post 2003)	2.12*** (2.84)	1.63*** (3.15)	1.28*** (3.84)

This table reports the annual alphas (in percentage) and their t -values (in parentheses) obtained from regressing monthly value-weighted PI portfolio returns on Fama–French five factors plus the momentum factor and the reversal factor. Annual alphas are obtained by multiplying monthly alphas by 12. We follow the technique from Jegadeesh and Titman (1993) to deal with holding periods longer than one month. The sample period is Jan 1980 to Dec 2024. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

We further evaluate investment profitability over longer holding horizons. Table 4 reports annualized alphas for value-weighted PI portfolios with holding periods of 3, 6, and 12 months, using the overlapping-portfolio procedure of Jegadeesh and Titman (1993) for horizons longer than one month.¹⁰ For each strategy, we first regress the monthly portfolio return on the Fama–French five factors, the momentum factor, and the short-term reversal factor, and then annualize the estimated monthly alpha by multiplying it by 12.

The long-short (top-minus-bottom) PI portfolio delivers positive and statistically significant alphas at all horizons. The annualized alpha equals 4.37% for the 3-month strategy ($t = 7.46$), 3.31% for the 6-month strategy ($t = 8.77$), and 2.23% for the 12-month strategy ($t = 8.67$). The decline in alpha as the holding period lengthens is gradual, and the t -statistics remain high, indicating that the profitability

¹⁰ For a K -month holding period, each month we rebalance $1/K$ of the portfolio formed in that month and carry forward the remaining $K - 1$ portions from previous months.

associated with PI is not confined to short holding periods. The post-2003 subsample exhibits the same pattern: alphas remain economically meaningful and statistically significant across all horizons.

To provide time-series perspective, we track the value of \$1 invested at the end of February 1980 in the value-weighted, monthly rebalanced PI long-short portfolio. Fig. 1 plots its cumulative performance together with the CRSP value-weighted market index. While \$1 invested in the market grows to \$27.25 by the end of the sample period, the PI strategy compounds to \$104.17, underscoring the economic significance and persistence of peer-based cross-stock predictability. The PI portfolio (blue line) outperforms the market benchmark (red line) throughout the sample period. By 2024, the PI strategy accumulates to more than 100 times the initial investment, whereas the market grows to roughly 30 times. This pattern highlights the economic relevance of the PI signal. The outperformance is especially pronounced during periods of market stress. During the Global Financial Crisis, while the market declined sharply, the PI portfolio was far more resilient: from February 2008 (the onset of the crisis according to FRED) to March 2009, the PI portfolio gained 19.7%, compared with a 38.3% drop in the market; over the broader crisis window, the market fell 22.6% whereas the PI portfolio experienced only a 10.4% drawdown. In the early-1980s “Volcker” recession, the PI portfolio rose 40.7% cumulatively; in the 1990–1991 recession it broadly preserved its value; and during the dot-com bust, the market fell 9.8% while the PI portfolio increased by 13.7%.

To compare downside risk, we compute the maximum rolling annual drawdown. At each month, we look back over the prior 12 months and record the largest peak-to-trough loss in cumulative returns within that window; the maximum annual drawdown is the largest of these 12-month losses over the full sample. The PI portfolio's maximum annual drawdown is −27.6%, compared with −46.3% for the market, indicating materially stronger downside resilience.

We recognize that leading practitioners have long recognized the use of industry growth prospects and relative standing in asset selection. For instance, BlackRock's iShares MSCI USA Quality Factor ETF tracks the MSCI USA Sector Neutral Quality Index, selecting high-quality stocks based on return on equity, earnings stability, and low leverage while maintaining sector neutrality. Similarly, the iShares S&P 500 Value ETF follows the MSCI USA Enhanced Value Index, identifying stocks with strong value characteristics using metrics like price-to-book, price-to-earnings, and enterprise value-to-cash flow. The iShares MSCI USA Momentum Factor ETF tracks the MSCI USA Momentum SR Variant Index, selecting the top 125 securities with the strongest momentum. Additionally, the BlackRock U.S. Industry Rotation ETF dynamically allocates investments across industries based on economic conditions. These ETFs exemplify BlackRock's integration of industry growth prospects and relative standing in investment strategies.¹¹

We obtain monthly returns for BlackRock's iShares MSCI USA Quality Factor, S&P 500 Value, and MSCI USA Momentum Factor ETFs.¹² We regress long-short PI portfolio returns on these ETFs to assess whether our approach yields abnormal returns. Table 15 reports loadings and alphas. Overall, while BlackRock ETFs capture some aspects of PI portfolio performance, positive and significant abnormal returns remain, underscoring the advantage of incorporating a broader set of peer-related characteristics and regularization techniques.

Taken together, these portfolio results show that the Peer Index (PI) delivers sizable and robust abnormal returns. The construction of the

PI involves both a large set of peer-based signals and a ridge regularization parameter that jointly determine the effective model complexity. An important question, therefore, is how portfolio and predictive performance vary with the degree of complexity and regularization.

To study this, we conduct a systematic complexity diagnostic following Kelly et al. (2024) and Didisheim et al. (2024), and construct value-of-complexity (VOC) curves that trace out predictive and portfolio performance as we vary both the number of signals P and the ridge penalty z . Performance is evaluated using the average return and annualized out-of-sample Sharpe ratio of the long-short PI portfolio, as well as the out-of-sample R^2 and mean squared prediction error of the PI-based forecasting model.¹³

The full PI construction includes up to $130 \times 2 = 260$ variables, corresponding to 130 peer averages and 130 within-peer deviations. We rank the signals by the magnitudes of their OLS coefficients and then expand the signal set gradually according to this ranking, considering $P \in \{20, 50, 100, 200, 260\}$.¹⁴

Fig. 2 reports the resulting VOC curves for ridge penalties $z \in \{10^{-5}, 10^{-3}, 10^{-1}, 1, 10\}$, as in Didisheim et al. (2024). The figure shows that performance initially improves as complexity rises, while the marginal gains attenuate once complexity exceeds an intermediate level. These results are best viewed as complementary, demonstrating that the way complexity pays off could be linked to the presence of economic structure.

3.4. Spanning tests

We follow the methodology in Ali and Hirshleifer (2020) to construct a new factor based on PI. At the end of each month, for our main sample, we divide stocks into big and small size groups based on whether their market capitalization is above or below the NYSE median market capitalization. Next, we calculate the value-weighted returns of the five quintile portfolios for each size group, and the factor is computed as

$$PIF = \frac{1}{2}(Ret_{big}^{PI,5} - Ret_{big}^{PI,1}) + \frac{1}{2}(Ret_{small}^{PI,5} - Ret_{small}^{PI,1}), \quad (14)$$

where $Ret_{big}^{PI,q}$ is the value-weighted average return of big-cap stocks in quintile q based on PI during the next month, and $Ret_{small}^{PI,q}$ is the value-weighted average return of small-cap stocks in quintile q based on PI during the next month. We term the factor as PIF.

We conduct a series of factor-spanning tests to assess whether existing factors can account for the new peer-based factor. Table 5 reports the alphas, factor loadings, and their t -values from these tests. The first set of factors we employ is the well-established five factors from Fama and French (2015). From the first row of the table, the PIF loads significantly on SMB, HML, and CMA. The monthly alpha is 1.00% and highly significant ($t = 3.32$).

Given the importance of past return variables in the index, our second test includes the FF5 factors alongside short-term reversal (REV), momentum (UMD), and liquidity (LIQ, Pástor and Stambaugh (2003)). The factor significantly loads on momentum. However, the alpha remains substantial at 0.74% ($t = 2.92$).

We also utilize the Daniel–Hirshleifer–Sun three-factor model (DHS3, Daniel et al. (2020)), which incorporates two behavioral factors, PEAD and FIN. Our analysis reveals that for PIF, the PEAD slope coefficient is notably strong at 0.45 ($t = 2.72$), underscoring the close association between these factors. The long-horizon FIN factor, on the other hand, does not play a role. Although the profitability of PIF is influenced by transient underpricing, the monthly alpha for PIF stands prominently

¹¹ BlackRock is used as an example; other major investment firms, such as J.P. Morgan, adopt similar strategies. For instance, the J.P. Morgan Large Cap Value Fund evaluates long-term company prospects to identify undervalued stocks based on valuation and temporary mispricings.

¹² These returns are available from August 2013, June 2000, and May 2013, respectively. The BlackRock U.S. Industry Rotation ETF is excluded due to insufficient data.

¹³ The rolling-estimation and out-of-sample forecasting procedures follow exactly those described in Section 3.2.

¹⁴ For robustness, we also rank signals by ridge coefficient magnitudes and by OLS t -statistics. All ranking methods yield very similar patterns.

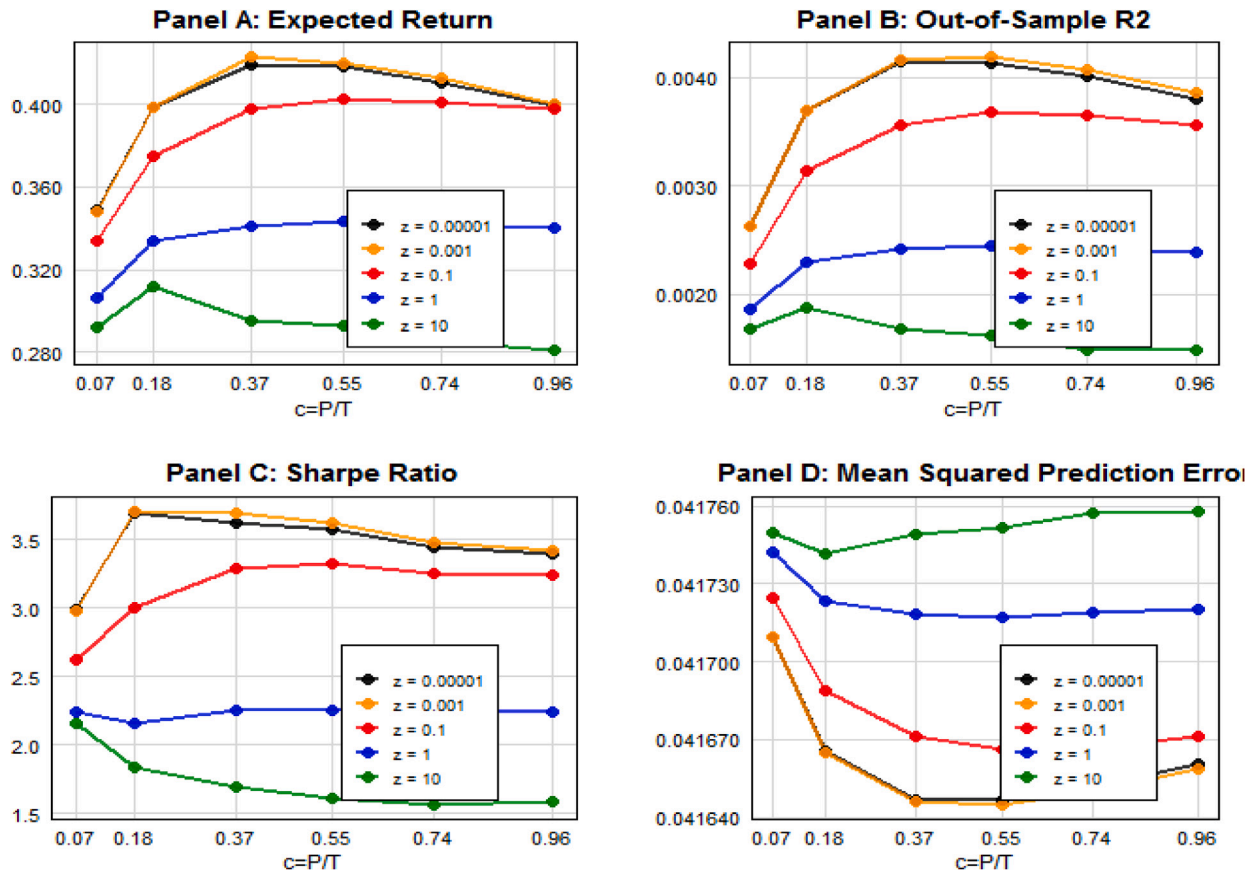


Fig. 2. Realized out-of-sample PI-based portfolio average return, Sharpe ratio, PI-based model out-of-sample R^2 , and mean squared prediction error. The horizontal axis shows model complexity $c = P/T$, with $P \in \{20, 50, 100, 200, 260\}$ and T is the average window size across all expanding windows.

Table 5

Alpha and factor loadings.

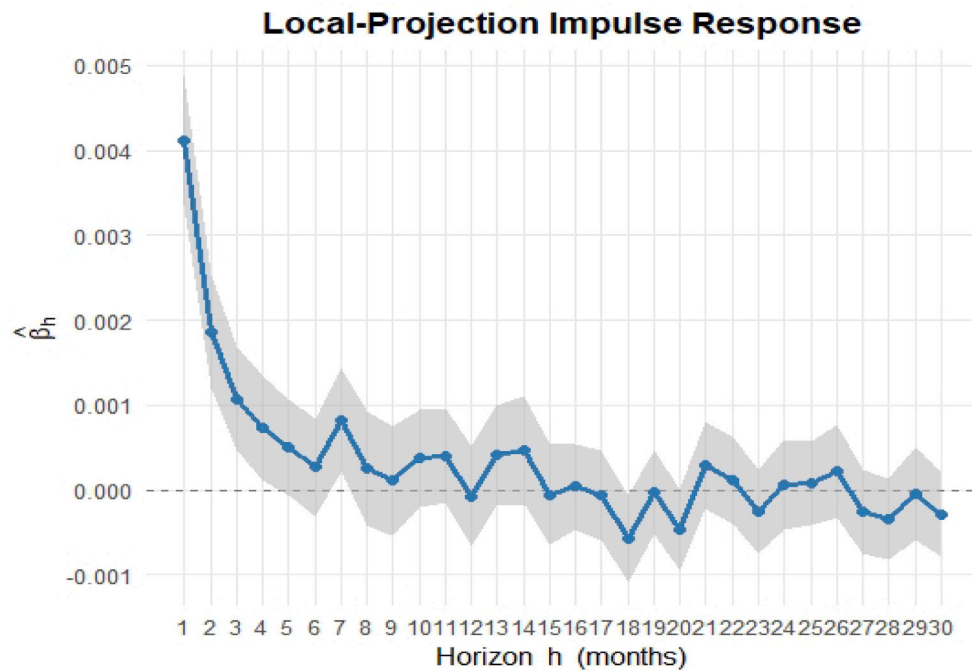
Alpha	Market	SMB	HML	RMW	CMA	UMD	REV	LIQ	PEAD	FIN	R_IA	R_ROE	MGMT	PERF
Panel (A): PIF														
1.00***	-0.18***	-0.28**	0.13	0.37***	0.25									
(3.32)	(-2.59)	(-2.40)	(1.18)	(2.61)	(1.35)									
0.74***	-0.02	-0.14	0.24***	0.45***	0.15	0.31***	-0.10	-0.02						
(2.92)	(-0.33)	(-1.42)	(2.60)	(3.77)	(0.96)	(6.31)	(-1.07)	(-0.62)						
1.06***	-0.19*								0.45***	0.03				
(3.19)	(-1.95)								(2.72)	(0.19)				
0.82***	-0.03	-0.07									0.49***	0.54***		
(3.23)	(-0.51)	(-0.64)									(4.36)	(5.45)		
0.94***	0.02	-0.04											0.31**	0.37***
(2.93)	(0.23)	(-0.33)											(1.93)	(4.69)
0.87**	-0.09	-0.16	0.28	0.78***	-0.64	0.35***	0.08	0.02	-0.07	-0.38**	0.71*	-0.26	0.23	0.09
(2.46)	(-0.62)	(-1.26)	(1.38)	(3.50)	(-1.59)	(3.14)	(0.44)	(0.53)	(-0.35)	(-2.33)	(1.70)	(-1.12)	(0.97)	(0.52)
Panel (B): PIF adjusted for machine learning														
0.95***	0.12***	-0.09**	0.12*	-0.16*	-0.10	0.12***	-0.34***	0.02	-0.04	-0.12*	0.27*	-0.03	0.22**	0.12**
(7.29)	(3.82)	(-1.97)	(1.74)	(1.70)	(-0.63)	(2.88)	(-8.89)	(0.85)	(-0.57)	(-1.74)	(1.79)	(-0.37)	(2.55)	(1.98)

This table reports the alphas, factor loadings, and their t-values (in parentheses) obtained from the factor-spanning tests of regressing the PI factor (PIF) on other factors. Panel (A) presents the results for the unadjusted PIF, while Panel (B) shows the results for the machine learning (ML)-adjusted PIF, where the predictive component driven by firm-specific characteristics is removed. The factors include FF5 factor, momentum factor (UMD), short-term reversal factor (REV), liquidity factor (LIQ) from [Pástor and Stambaugh \(2003\)](#), short-horizon inattention factor (PEAD) and long-horizon financing factor (FIN) from [Daniel et al. \(2020\)](#), investment factor (R_IA) and return on equity factor (R_ROE) from [Hou et al. \(2015\)](#), management factor (MGMT) and performance factor (PERF) from [Stambaugh and Yuan \(2017\)](#). PEAD and FIN are available from January 1980 to December 2018. MGMT and PERF are available from January 1980 to December 2016. All other factors are available during the whole sample period. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

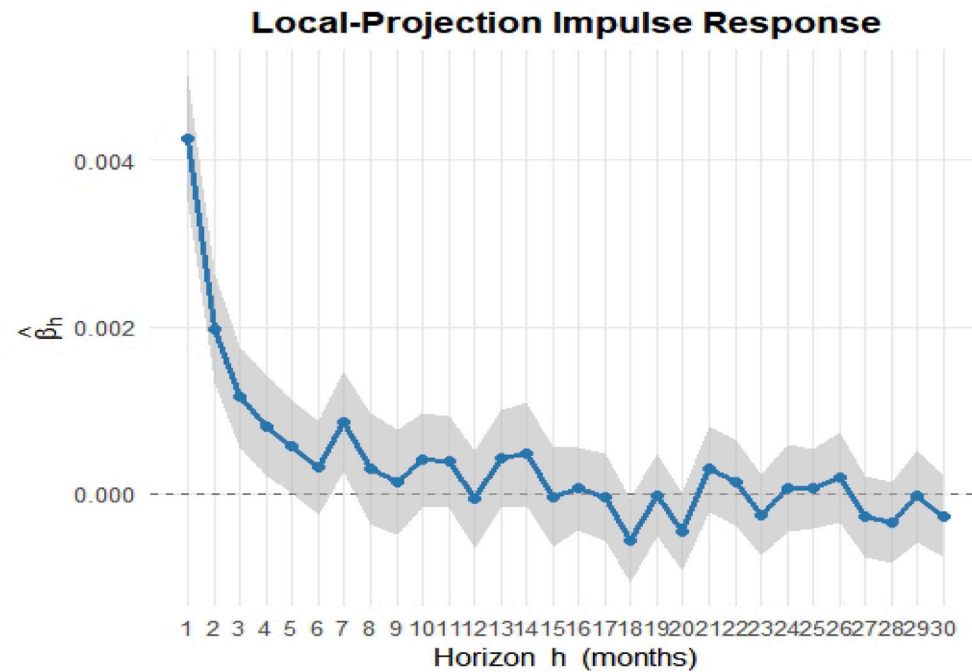
at 1.06% ($t = 3.19$). These findings demonstrate that our peer-based factor offers valuable incremental insights alongside the short-horizon and long-horizon systematic mispricing identified by the DHS3 factor model.

Next, we analyze the Hou-Xue-Zhang four-factor model (HXZ4, [Hou et al. \(2015\)](#)), which adds an investment factor (R_IA) and return

on equity factor (R_ROE) to the size and market factor. This model significantly explains many anomalies. This model demonstrates robust explanatory power over PIF, with both R_ROE and R_IA showing significant and substantial coefficients in the PIF regression. The four-factor alpha is 0.82% ($t = 3.23$).



(a) Panel A: Impulse response of $PI_{i,t}$ on future returns $R_{i,t+h}$ with a 95% confidence interval for horizons $h = 1$ to 30 months. PI is scaled by 10.



(b) Panel B: Impulse response of $PI_{i,t}$ shocks on future returns $R_{i,t+h}$ with a 95% confidence interval for horizons $h = 1$ to 30 months. The shock variable is scaled by 10.

Fig. 3. Lag-Augmented Local Projection (LA-LP).

We then consider the Stambaugh and Yuan four-factor model (SY4, [Stambaugh and Yuan \(2017\)](#)), which consolidates 11 anomalies into two composite mispricing factors, MGMT and PERF.¹⁵ This model demonstrates robust explanatory power over PIF, with both mispricing

¹⁵ We have scaled the original factor returns by 100 for percentage compatibility, aiding coefficient comparability.

factors showing significant and large coefficients in the PIF regression. The monthly alpha of PIF is 0.94% ($t = 2.93$).

We also consider all 14 factors in an all-inclusive model. The alpha of PIF is 0.87% ($t = 2.46$). Hence, the peer-based factor carries substantial return predictability even after controlling for a large set of known factors, underscored by consistently large positive alphas across all examined factor models.

Lastly, to assess the incremental information in PIF beyond flexible nonlinear machine learning models that rely solely on firm-specific characteristics, we isolate the cross-predictability component of PI and construct an ML-adjusted PIF. Following a similar approach to the portfolio analysis, we regress returns on the PI signal against expected return proxies generated by a neural network model, which utilizes 130 firm-specific characteristics. We then remove the fitted component associated with this machine-learning approach, retaining only the alpha and residual as our new signal. Finally, we construct the ML-adjusted PIF by substituting the refined signal into Eq. (14). The results for the all-inclusive test are reported in Panel B of Table 5. The alpha of PIF remains high at 0.95% ($t = 7.29$), confirming that adjusting for predictability from firm-specific characteristics using a flexible machine-learning method does not alter our findings.

3.5. Dynamic response to PI shocks

The portfolio and Fama–MacBeth results above show that the Peer Index (PI) contains powerful *cross-sectional* information: firms with high PI earn higher subsequent returns, and long–short portfolios sorted on PI deliver large, persistent alphas. What these tests do not reveal is the *time path* of price adjustment to a peer-information surprise. Our interpretation of PI is that it captures information that diffuses across economically linked firms only gradually. If this interpretation is correct, a positive PI surprise should be followed by an immediate return increase, a short period of decaying positive effects, and — crucially — no subsequent reversal. Fig. 3 is intended to document exactly this dynamic adjustment and to connect the cross-sectional findings to a price-formation mechanism.

To trace the response of returns to a PI innovation, we follow the shock-impulse-response logic outlined in Kogan and Papanikolaou (2013, 2014) and implement the lag-augmented local projections (LA–LP) of Montiel Olea and Plagborg-Møller (2021). The advantage of LA–LP here is that we can work directly with PI in levels and let the projection partial out rich dynamics by adding lags of all series, instead of having to construct explicit shocks/innovations for each firm–month.

For each horizon $h = 1, \dots, 30$, we estimate the following panel regression with firm fixed effects:

$$R_{i,t+h} = \alpha_i + \beta_h PI_{i,t} + \theta_h R_{i,t} + \phi_h Size_{i,t} + \psi_h BM_{i,t} + \sum_{\ell=1}^{12} (a_{h,\ell} R_{i,t-\ell} + b_{h,\ell} PI_{i,t-\ell} + c_{h,\ell} Size_{i,t-\ell} + d_{h,\ell} BM_{i,t-\ell}) + e_{i,t+h}, \quad (15)$$

where $R_{i,t}$ is the stock return, $PI_{i,t}$ is the peer-information signal, and $Size_{i,t}$ and $BM_{i,t}$ are standard firm controls. We include 12 monthly lags of all variables, as suggested by Montiel Olea and Plagborg-Møller (2021), to capture short-run dynamics in monthly data. The coefficient β_h is the local-projection estimate of the impulse response of returns h months ahead to a one-unit change in PI at time t . Heteroskedasticity-robust standard errors are used to construct confidence bands.

Panel A of Fig. 3 reports the estimated impulse responses. For interpretation, we rescale PI to the interval $[-0.5, 0.5]$ and then multiply it by 10, so that a one-unit move corresponds to a 10-percentile increase in the cross-sectional PI rank. At $h = 1$, a 10-percentile increase in PI raises next-month returns by about 0.40%, and the estimate is statistically significant. The effect then declines smoothly and becomes indistinguishable from zero after about five to six months. Importantly, the responses do *not* turn negative at longer horizons. This pattern is what we would expect if markets gradually incorporate information coming from economically connected peers: there is an immediate positive effect, some short-lived continuation as the information diffuses across firms, and no evidence of later overreaction or microstructure-induced reversal.

LA–LP also allows us to check that the pattern is not an artifact of persistence in PI. When true innovations are observed, running the projection directly on the innovation and its lags should deliver the same impulse responses. Following Kogan and Papanikolaou (2013, 2014), we therefore construct PI innovations as the residuals from an AR(1) process (and, as a robustness check, using simple first differences) and re-estimate Eq. (15) with the innovation in place of $PI_{i,t}$. Panel B of Fig. 3 shows that the short-run hump and the absence of long-run reversal remain. This confirms that the dynamic pattern in Fig. 3 reflects the market's reaction to *unexpected* peer information rather than to slow-moving, already-priced components of PI.

Taken together, these dynamic results show that peer-based information is priced in a way that is fast but incomplete: a PI surprise is followed by an immediate positive return, some short-lived continuation, and no subsequent reversal. What the analysis has not yet established is *what* economic news PI is conveying — whether it anticipates future cash-flow realizations in the peer group, captures discount-rate movements tied to industry conditions, or instead reflects investor attention and sentiment. To open up this mechanism, the next section examines how PI lines up with subsequent earnings surprises and industry returns, and then asks whether the return premium associated with PI can be reconciled with standard risk or sentiment explanations.

4. Economic rationale

4.1. Information content of PI

To fully understand the predictive power of the Peer Index (PI), we examine its relationship with both industry- and firm-level fundamentals, highlighting its role in forecasting future cash flows and discount rates.

We first examine the relationship between PI and industry-level earnings surprises and industry returns. To measure earnings surprises, we adopt the standardized unexpected earnings (SUE) metric from Rendleman Jr. et al. (1982), which is computed as the I/B/E/S actual earnings minus the median forecasted earnings, divided by the fiscal-quarter-end market capitalization.¹⁶ We use the equal-weighted average to construct industry-level earnings variables.

Following a similar approach to Ali and Hirshleifer (2020), we conduct predictive regressions for industry-level fundamentals, specified as follows:

$$SUE_{ind,i,t+1} = \beta_1 PI_{i,t} + \beta_2 ML_{i,t} + FE + \text{controls} + e_{i,t+1}. \quad (16)$$

The dependent variable, $SUE_{ind,i,t+1}$ represents one-quarter-ahead standardized unexpected earnings (SUE) for the industry of stock i . The main explanatory variable of interest is $PI_{i,t}$, representing the average of monthly PI in the current quarter. We also include the average of monthly machine learning forecast in the current quarter, denoted as $ML_{i,t}$.¹⁷ We include current industry level SUE ($SUE_{ind,i,t}$) as control variables, along with industry-average size and book-to-market ratios. Quarter fixed effects and stock fixed effects are included. To facilitate interpretation, all independent variables are cross-sectionally standardized to $[-0.5, 0.5]$.

Beyond fundamentals, we also investigate whether PI predicts future industry-level returns using Fama–MacBeth regressions. The dependent variable is the one-month-ahead industry equal-weighted average return. Apart from the ML prediction, we also control for lagged

¹⁶ If an earnings forecast is unavailable, the unexpected earnings are computed as the I/B/E/S actual earnings minus the seasonally differenced quarterly earnings.

¹⁷ As a robustness check, we also run the regression using the most recent monthly PI and ML forecast available before the end of the current quarter, and the result is robust.

Table 6
Predicting industry-level fundamentals & Returns.

	$SUE_{ind,i,t+1}$	$R_{ind,i,t+1}$
PI	0.004*** (22.27)	0.920*** (8.61)
ML	0.001*** (5.77)	0.165 (1.52)
Controls	Yes	Yes
Fixed effect	Yes	Yes
Adjusted R ²	0.067	0.112
Observations	639,525	2,086,995

This table reports the results of panel regression for predicting one-step-ahead earnings surprises and excess returns at the industry level. The earnings surprise is measured by the standardized unexpected earnings (SUE), which is computed as the I/B/E/S actual earnings minus median forecasted earnings divided by fiscal-quarter-end market cap. If earning forecast is not available, then the unexpected earning is computed as the I/B/E/S actual earnings minus the seasonally differenced quarterly earnings. In the regression for predicting one-step-ahead earnings surprises, we include both time and entity fixed effects. Control variables include current industry average SUE, together with industry average size and book-to-market. *t*-statistics based on standard errors clustered by entity are shown below coefficient estimates. The second column of the table shows the average slopes*100; *t*-statistics with Newey–West adjustments of 12 lags from monthly Fama–MacBeth regressions for industry return. Control variables include lagged industry-average returns, industry-average size, and the book-to-market ratio. All explanatory variables are cross-sectionally standardized. The adjusted R² is the average across all cross-sectional regressions. For brevity, the coefficients on these controls are not reported. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

industry-average returns, industry-average size and book-to-market ratio.

Table 6 presents the results. The first column of the table shows that PI significantly predicts future industry-level earnings surprises, even after controlling for lagged industry variables. By contrast, the ML variable has a much smaller coefficient and is far less significant. The industry-level Fama–MacBeth regressions confirm that PI positively predicts future industry returns beyond traditional factors, while ML-based variable fails to predict industry returns. Taken together, these findings suggest a strong relationship between the Peer Index (PI) and industry strength—both in terms of fundamentals and returns.

Next, we turn to firm-level analysis and examine the future cash flow implications of the peer-based index using the following fixed-effects panel regression:

$$SUE_{i,t+h} = \beta_1 PI_{i,t} + \beta_2 ML_{i,t} + FE + \text{controls} + \epsilon_{i,t+h}, \quad (17)$$

$SUE_{i,t+h}$ represents the standardized unexpected earnings (SUE) for stock *i* at quarter *t* + *h*. We consider one-, four-, and eight-quarter-ahead predictions (i.e., *h* = 1, 4, 8). Our primary explanatory variable of interest is $PI_{i,t}$, the average of monthly PI in the current quarter. We also include the average of monthly machine-learning forecasted return for stock *i* in quarter *t*, denoted as $ML_{i,t}$.¹⁸ Control variables include the firm's current $SUE_{i,t}$ and its industry-average counterpart. Both regressions incorporate individual and quarter fixed effects, along with additional control variables such as size and the book-to-market ratio.

Table 7 presents the estimation results. Column 1 shows the estimates for predicting one-quarter-ahead earnings surprises. PI and the machine-learning forecasted return variable exhibit similar coefficients, both positively and significantly predict future earnings surprises one-quarter-ahead.

Column 2 examines the predictive power of the variables for four-quarter-ahead SUE, where PI continues to show a positive relationship with future earnings surprises. The machine-learning variable, on the other hand, has a negative coefficient. This pattern persists for eight-quarter-ahead SUE, as shown in Column 3.

In summary, even after explicitly controlling for a firm's lagged earnings variable, the lagged industry average, and a flexible machine-learning variable that captures high-dimensional firm-specific characteristics, the Peer Index (PI) remains a significant predictor of both short- and long-horizon earnings surprises. These findings align with broader evidence that PI robustly predicts long-horizon returns, reinforcing its role as a valuable predictor of industry strength and a firm's relative positioning within the industry.

4.2. Under-reaction

What is the source of PI predictability? As shown in Table 3, although PI-based portfolios exhibit significant loadings on some common factors, their risk-adjusted alphas remain highly significant, both economically and statistically. This suggests that the PI effect is not merely a consequence of exposure to traditional asset pricing factors. Moreover, PI significantly predicts future returns and earnings surprises, even after controlling for flexible machine learning signals, suggesting that PI captures cross-stock predictability that extends well beyond individual predictive characteristics.

Could cross-stock predictability by PI be attributed to overreaction? Numerous studies have linked asset pricing anomalies to investor overreactions in different contexts. For example, De Bondt and Thaler (1985) in their seminal work suggested that an initial overreaction to negative news, which later corrects itself, leads to reversal. Jegadeesh and Titman (1995) documented that most contrarian profits stem from investor overreactions to firm-specific information. Recent evidence on overreactions includes Huang et al. (2018), Bordalo et al. (2020) and Da et al. (2021), among others. If overreaction is driving the PI effect, then we should observe a reversal in returns.

However, from Panel C of Table 1, the coefficient of PI is consistently positive across all investment horizons examined, indicating that it can positively predict long-term returns without reversal, which contradicts the overreaction hypothesis. Moreover, the impulse response analysis in Fig. 3 likewise shows no evidence of return reversal at longer horizons.

Could the predictability of PI arise due to sentiment investing? Since PI captures industry strength and a stock's relative position within its industry peer group, it may overlap with stock-level and industry-level sentiment. To demonstrate that the predictability of the Peer Index (PI) is not driven by sentiment effects, we utilize the RavenPack News Analytics dataset to construct a stock-level sentiment index and employ a bottom-up approach to derive industry-level sentiment indices.¹⁹

Our analysis reveals that the correlation between PI and the stock-level news-based sentiment index is −0.029, while the correlation between PI and the industry-level news-based sentiment index is −0.003. Additionally, Table 16 in the Appendix presents results from value-weighted Fama–MacBeth (FM) regressions incorporating the constructed stock-level and industry-level sentiment indices. Control variables include the past one-month return, the past 12-month return (excluding the most recent month), size, and book-to-market ratio. At 5% significance level, both sentiment indices fail to predict one-month-ahead returns when basic control variables are included. Meanwhile, PI remains statistically significant even after controlling for sentiment indices and all other variables. These results suggest that PI captures information distinct from sentiment effects.

We hypothesize that underreaction to peer-related information is the primary driver of the predictability of PI. Financial markets inadequately incorporate information from peers because standard asset

¹⁹ The RavenPack News Analytics dataset has been available since 2000. It identifies companies mentioned in news items and assesses article-specific sentiment. For the monthly stock-level sentiment index, we compute the average daily sentiment for each stock within a given month. For the monthly industry-level sentiment index, we aggregate company-specific sentiment into industry-wide sentiment using a simple average.

¹⁸ We use NN3 here, as it outperforms GBRT and RF in previous analyses.

Table 7
Predicting firm-level earnings surprises.

	(1) One-quarter-ahead	(2) Four-quarter-ahead	(3) Eight-quarter-ahead
PI	0.026*** (21.29)	0.0112*** (9.28)	0.001*** (2.90)
ML	0.027*** (16.74)	−0.009*** (−8.00)	−0.008*** (−6.55)
Observations	639,525	608,144	556,180
Adj. R^2	0.032	0.028	0.023
Controls	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes

This table reports the results of panel regression for predicting multiple-step-ahead earnings surprises. The earnings surprise is measured by the standardized unexpected earnings (SUE), which is computed as the I/B/E/S actual earnings minus the median forecasted earnings divided by fiscal-quarter-end market cap. If earning forecast is not available, then the unexpected earning is computed as the I/B/E/S actual earnings minus the seasonally differenced quarterly earnings. Control variables include the firm's current $SUE_{i,t}$ and its industry-average counterpart, along with size and the book-to-market ratio. Both regressions incorporate individual and quarter-fixed effects. All explanatory variables are cross-sectionally standardized. For brevity, the coefficients on these controls are not reported. t -statistics based on standard errors clustered by entity are shown below coefficient estimates. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

pricing and forecasting models do not fully comprehend network effects among firms. Controlling for firm-own characteristics, these models treat stocks as independent entities rather than as interconnected nodes within an economic system.²⁰ This structural limitation leads to a persistent underreaction. The empirical results support this: PI predicts earnings surprises even after controlling for machine learning-based predictors, demonstrating that markets adjust too slowly to industry-wide information. Investors and analysts emphasize firm-level fundamentals but make only limited adjustments based on peer information, even when industry-wide signals provide leading information about future firm performance.

If the predictability of the Peer Index (PI) is driven by underreaction, its effect should be more pronounced when information uncertainty is greater and investor attention is lower. We measure information uncertainty using both the number of analysts covering a firm and the dispersion in analysts' forecasted EPS, following Diether et al. (2002), Barron and Stuerke (1998), Zhang (2006), and Hou (2007). When a firm faces higher information uncertainty, processing its information becomes more costly, leading to slower market reactions to news about the firm. Next, we capture the role of investor attention. Investors' limited attention and cognitive constraints are key drivers of underreaction-type anomalies. Using media coverage as a proxy for investor attention, Chen et al. (2023) document that underreaction-related anomalies are significantly more pronounced among firms with low media coverage in the previous month. Following their approach, we use the RavenPack News Analytics dataset to construct two news-based attention measures. The first measure is the monthly number of news articles mentioning a particular firm. Since analyst coverage and news volume are positively correlated with firm size, we also construct an alternative measure that captures shifts in attention while mitigating the pure size effect. This second measure is the change in the number of news mentions, calculated as the difference between the current and previous month's news mentions. Both news-based attention measures are available starting in 2000, when the RavenPack dataset became accessible. Finally, we control for the size effect.

Using a 70/30 split, we categorize stocks into two groups each month based on each variable's value at $t - 1$. For size, the number of analysts, news mentions and monthly change in news mentions, a smaller value indicates slower information transmission. We create an indicator variable equal to 1 if the stock is below the bottom 30%,

and 0 otherwise. For analyst dispersion, a larger value indicates more information uncertainty and slower information diffusion, so we create an indicator variable equal to 1 if the stock is above the top 30%, and 0 otherwise. We then interact each of these dummy variables with PI in the Fama–MacBeth regression to capture the effect of under-reaction and slow information diffusion.

Table 8 presents the results of the heterogeneity tests. For the Peer Index (PI), all five interaction terms are individually significant with a positive sign. When we include all the proxy variables simultaneously in the regression, size, news mentions, and changes in news mentions remain significant at the 10% level with a positive sign. These results indicate that while underreaction to peer-related information is a broad market phenomenon, its severity varies across stocks, being most pronounced among firms that have greater information uncertainty, and receive lower investor attention. Overall, the evidence supports the underreaction and slow information diffusion hypothesis.

5. Asymmetric networks

The literature has developed a variety of proxies for inter-firm linkages and networks. Beyond the industry affiliations used in our main analysis (Moskowitz and Grinblatt, 1999; Hong et al., 2007), two asymmetric networks — customer-supplier links (Cohen and Frazzini, 2008) and shared-analyst co-coverage (Ali and Hirschleifer, 2020) — are also widely studied. In this section, we ask two questions using these asymmetric networks: (i) can our Peer Index (PI) be explained by cross-firm momentum effects operating through these channels? and (ii) within the symmetric–antisymmetric decomposition of Kelly et al. (2023), which component drives our results?

We focus on these two types of asymmetric networks because they cover a relatively large share of firms in our sample. As summarized by Yan and Yu (2023), more than 2500 U.S. firms exhibit these linkages, whereas other asymmetric connections — for example, conglomerate–standalone ties (Cohen and Lou, 2012) — are sparser and cover far fewer firms.

5.1. Cross-firm momentum effects

We show earlier that two industry-level effects — industry momentum and industry lead-lag — do not subsume the explanatory power of PI; if anything, PI subsumes both. Recent studies document that peer firms' past returns help explain a focal firm's future returns, i.e., cross-firm momentum effects. We therefore test whether cross-firm momentum operating through shared-analyst coverage or supply-chain links can account for PI.

²⁰ We acknowledge that some research has considered peer effects. However, these studies often focus on a single dimension, such as peers' past returns, providing only a partial perspective, which still leads to underreaction due to the complex role that peer information plays in asset pricing.

Table 8
Cross-sectional variation in PI effect.

Dependent variable: One-month-ahead return						
	(1)	(2)	(3)	(4)	(5)	(6)
PI	0.93*** (3.68)	2.46*** (10.04)	2.87*** (8.11)	2.39*** (7.97)	1.52*** (5.44)	1.64*** (5.73)
PI*Dummy(Size < 30%)	2.27*** (4.10)	2.13*** (10.95)				
PI*Dummy(Analyst < 30%)	0.10 (0.22)		1.20*** (5.73)			
PI*Dummy(Dispersion > 70%)	0.28 (1.10)			0.82*** (4.98)		
PI*Dummy(News < 30%)	0.92*** (3.16)				1.28*** (5.97)	
PI*Dummy(Δ News < 30%)	0.42* (1.69)					0.83*** (3.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Average# of stocks	3895	3963	3963	3963	3895	3895
Average adjusted R^2	0.051	0.036	0.034	0.042	0.040	0.040

This table reports regression results of the heterogeneity tests. We use five variables to proxy the speed of information flow, including size, number of analysts, analyst dispersion, news mentions and change in news mentions. The two news-based attention variables are available since 2000. For size, number of analysts, news, and Δ news, we create an indicator variable equal to 1 if the stock is below the bottom 30%, and 0 otherwise. For analyst dispersion, we create an indicator variable equal to 1 if the stock is above the top 30%, and 0 otherwise. In columns 2–6, we conduct FM regression by regressing future returns on PI and one of the interaction terms. In column 1, we conduct FM regression by regressing future returns on PI and all five interaction terms. Control variables include past one-month return, past 12-month return (excluding the most recent month), size and book-to-market. FM coefficients are the means of the monthly estimated coefficients*100; t -statistics employ Newey–West adjustments of 12 lags.

We construct analyst co-coverage linkages in the same way as [Ali and Hirshleifer \(2020\)](#), utilizing I/B/E/S analyst forecast data. In each sample month, two firms are defined as linked if at least one analyst covers both stocks. A stock is considered covered by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the stock over the prior 12 months.²¹ For each stock i , we calculate its signal, denoted SA_Ret , as the weighted average return of all stocks linked to it during the month, with weights proportional to the number of shared analysts.

The customer–supplier data is sourced from the Compustat Customer Segment File. Following [Cohen and Frazzini \(2008\)](#), principal customers are matched to the CRSP sample. An equally weighted portfolio of the corresponding customers, based on the last available supplier–customer link, is constructed with a six-month lag to ensure that the linkage information is public. The portfolio return is denoted as Cus_Ret .²²

We cross-sectionally standardize all signals before running the value-weighted Fama–MacBeth regressions to ensure comparability of coefficients. Control variables include past one-month return, past 12-month return (excluding the most recent month), size and book-to-market. The results are shown in [Table 9](#). As seen in [Table 1](#), our PI signal subsumes the predictive power of industry effects. Upon adding PI to the Fama–MacBeth regression, both industry terms are not significant at 5% level. The lead–lag effect via shared-analyst linkages is a strong source of cross-predictability. While [Ali and Hirshleifer \(2020\)](#) documented that this form of cross-stock momentum unifies all other forms of momentum spillover factors proposed in the literature, we find the information content of the shared-analyst signal and PI to be distinct, with a correlation of 0.048. Controlling for this recently proposed cross-stock momentum signal, the Fama–MacBeth coefficient

Table 9
Cross firm momentum effects and Fama–MacBeth cross-sectional regressions.

Dependent variable	Observations	PI	INDMOM	Lead-lag	SA_Ret	Cus_Ret
R_{t+1}	2,088,332		0.21 (1.40)			
R_{t+1}	2,088,332	0.98*** (6.53)	0.07 (0.39)			
R_{t+1}	2,088,332			0.56** (3.52)		
R_{t+1}	2,088,332	0.86*** (6.45)		0.31* (1.72)		
R_{t+1}	1,674,481				1.03*** (4.62)	
R_{t+1}	1,674,481	0.84*** (7.20)			0.86*** (3.81)	
R_{t+1}	2,000,816					0.39*** (2.90)
R_{t+1}	2,000,816	0.72*** (5.50)				0.36*** (2.60)
R_{t+1}	1,674,481	0.87*** (5.92)	−0.57* (−1.88)	0.13 (0.46)	0.90*** (3.89)	0.24 (1.61)

The table shows the average slopes*100; t -statistics with Newey–West adjustments of 12 lags from monthly value-weighted Fama–MacBeth regressions. Control variables include size, book-to-market ratio, short-term reversal, and momentum. The sample period is January 1980–Dec 2024. For the main sample, we exclude “nano” stocks whose market capitalization is below the 1st percentile of the NYSE sample. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

of PI is 0.84, with a t -statistic exceeding seven. Customer momentum ([Cohen and Frazzini, 2008](#)) also shows significant predictive power for future returns. Again, this signal has low informational overlap with our peer-based index, with a correlation coefficient as low as 0.007. When including the customer momentum signal, the Fama–MacBeth coefficient of PI remains at 0.72, with a t -statistic exceeding five.

Finally, when all variables are included, PI remains robust, indicating that it captures additional predictive information beyond traditional linkages. In contrast, the two industry-level terms and the customer momentum variable lose statistical significance. In summary, the Peer Index is not fully explained by existing cross-firm effects and provides unique insights into future stock returns.

²¹ The resulting co-coverage adjacency matrix $L^{analyst}$ is symmetric, with $L_{ij}^{analyst} = L_{ji}^{analyst}$ equal to the number of shared analysts between i and j . To construct the peer-average signal in [Ali and Hirshleifer \(2020\)](#), one needs to row-normalize $L^{analyst}$ to obtain $L_{normalized}^{analyst} = D^{-1} L^{analyst}$, where $D = \text{diag}(d_i)$ and $d_i = \sum_j L_{ij}^{analyst}$. Because degrees d_i vary across firms, $L_{normalized}^{analyst}$ is generally asymmetric.

²² We thank Hong Xiang for kindly providing us the cleaned customer–supplier data used in [Huang et al. \(2022\)](#).

Table 10
PI components under an asymmetric network.

Component	Type	Economic meaning
$L_{\text{sym}}\mathbf{x}_t$	Symmetric	Beta on factor implied by the characteristic
$L_{\text{asym}}\mathbf{x}_t$	Antisymmetric	Alpha/cross-directional timing
$(I - L_{\text{sym}})\mathbf{x}_t$	Symmetric	Beta on factor implied by the peer-adjusted characteristic
$(I - L_{\text{asym}})\mathbf{x}_t$	Mixture	Own-signal beta + alpha from peer-adjusted strategy

5.2. Symmetric–antisymmetric decomposition

As detailed in Section 2, our baseline PI constructs the peer network using SIC-based industry linkages. This construction delivers a position matrix L^{ind} that is *symmetric* in the strict sense that $L_{ij}^{\text{ind}} = L_{ji}^{\text{ind}}$ for all firms i, j . For a symmetric L , the symmetric–antisymmetric decomposition of Kelly et al. (2023) collapses to its symmetric component, and the antisymmetric arm is mechanically zero. This does *not* imply the absence of cross-predictability. On the contrary, PI effectively operates through an industry-peer channel: each firm's signal loads on the information of its SIC peers, so both the peer-average component and the deviation-from-peers component can forecast returns. What symmetry rules out is specifically *directional* peer effects of the leader–follower type. Because the SIC network is symmetric, any alpha that relies on asymmetric links cannot arise in this specification.

To study what happens once the peer network is asymmetric, we apply the symmetric–antisymmetric decomposition to: (i) the shared-analyst network of Ali and Hirshleifer (2020) and (ii) the customer–supplier network of Cohen and Frazzini (2008). For these networks, L is no longer symmetric, so both arms of the decomposition are active and we can explore which one actually drives out-of-sample performance.

Formally, for a signal vector $\mathbf{x}_t \in \mathbb{R}^N$ (for simplicity, we suppress the characteristic index s in the subscript in this section) and an asymmetric position matrix L , write

$$L_{\text{sym}} = \frac{1}{2}(L + L'), \quad L_{\text{asym}} = \frac{1}{2}(L - L'), \quad L = L_{\text{sym}} + L_{\text{asym}}. \quad (18)$$

We then construct four components — peer averages and within-peer deviations — based on L_{sym} and L_{asym} separately. First, applying L to $\mathbf{x}_t$ gives two peer-average legs,

$$\mathbf{z}_{\text{sym}} = L_{\text{sym}}\mathbf{x}_t, \quad \mathbf{z}_{\text{asym}} = L_{\text{asym}}\mathbf{x}_t. \quad (19)$$

The first is a factor-exposure (beta) strategy to the latent factor implied by the characteristic; the second, the directional peer-average component, captures the factor-neutral, timing-type effect emphasized in the principal-portfolio framework.

Our peer-adjusted signal is $(I - L)\mathbf{x}_t$. Let $M = I - L$, where I is the identity matrix. Then

$$M_{\text{sym}} = \frac{1}{2}(M + M') = I - L_{\text{sym}}, \quad M_{\text{asym}} = \frac{1}{2}(M - M') = -L_{\text{asym}}, \quad (20)$$

so the peer-adjusted strategy decomposes as

$$(I - L)\mathbf{x}_t = (I - L_{\text{sym}})\mathbf{x}_t + (-L_{\text{asym}})\mathbf{x}_t. \quad (21)$$

In words, $(I - L_{\text{sym}})\mathbf{x}_t$ is the *beta* leg built from peer-adjusted characteristic, while $-L_{\text{asym}}\mathbf{x}_t$ is the *alpha* leg inherited from the asymmetric part of the network. Our fourth component, $(I - L_{\text{asym}})\mathbf{x}_t$, combines the own-signal beta with the alpha leg from the peer-adjusted strategy. Table 10 summarizes the four components.

Because these four objects are perfectly linearly related, we conduct a drop-one-out experiment to assess component importance. For a given *asymmetric* network (shared analysts or customer–supplier), we (i) drop one component at a time (in the multi-characteristic case, we drop all transformed variables in that category); (ii) build PI from the remaining three; and (iii) compare out-of-sample R^2 and long–short portfolio returns. The logic is straightforward: if a component matters, then dropping it should lead to both poor fit and portfolio performance.

Table 11
Drop-one-out analysis.

Specification	(A) Analyst-network		(B) Customer–supplier	
	OOS R^2 (%)	Port_ret (%)	OOS R^2 (%)	Port_ret (%)
Drop_sym_peer	0.2498	2.898	0.1798	2.467
Drop_sym_dev	0.2504	2.875	0.1808	2.477
Drop_asym_peer	0.2437	2.860	0.1747	2.430
Drop_asym_dev	0.2604	2.938	0.1768	2.510

The table reports out-of-sample performance of drop-one-out PI indices based on the shared-analyst or customer–supplier networks. In each specification, we exclude one component (in the case of multiple characteristics, all transformed variables for $s = 1, \dots, S$ within that category) and construct the PI index using the remaining three components. Out-of-sample R^2 (%) is computed using a rolling estimation window of 84 months, as described in Section 3.2. The long–short equal-weighted portfolios are formed following the procedure in Section 3.3.

Table 11 reports the drop-one-out analysis results. Two findings emerge. First, for the shared-analyst network, the *antisymmetric peer-average* component is the most valuable one: removing it produces the sharpest deterioration in both R^2 and returns. This means that, once the peer graph admits asymmetry, the factor-neutral, cross-directional timing embedded in $L_{\text{asym}}\mathbf{x}_t$ becomes an important source of predictability. The *symmetric peer-deviation* component comes next: dropping it modestly weakens performance, which is consistent with analyst co-coverage creating tight economic benchmarking (Kaustia and Rantala, 2021). By contrast, the *antisymmetric deviation* sleeve adds the least and can even introduce noise, since omitting it leads to the highest R^2 and returns.

Second, for the customer–supplier network, the pattern is similar but economically even more intuitive: direction runs from customers to suppliers, so characteristics averaged over customers help forecast suppliers' returns; deviations from those customer averages are less informative. Accordingly, both deviation components (symmetric and antisymmetric) play a limited role, while the antisymmetric peer-average component again carries most of the predictive content.

Put together, this section clarifies why the baseline, SIC-based PI is purely symmetric (the network itself is symmetric), and it shows that once we move to genuinely asymmetric peer structures, the antisymmetric, factor-neutral arm can be an important engine of PI-type strategies.

6. Conclusion

This paper develops an economically structured measure of cross-stock return predictability. Starting from observable firm linkages — most prominently SIC-based industry classifications, as well as shared-analyst coverage and customer–supplier networks — we construct the Peer Index (PI), which maps information from a stock's peers into its own expected return. The construction delivers two distinct and interpretable channels: (i) a *peer-average* channel, through which firms inherit information embedded in their economic network, and (ii) a *deviation-from-peers* channel, through which characteristics that are unusual relative to the peer group average convey additional information. Building cross-predictability directly into the signal in this way allows us to speak to *why* one firm's characteristics should help forecast another firm's return.

A central empirical result is that PI remains strongly predictive even after we control for powerful machine-learning expected-return proxies constructed from a large set of firm-level characteristics. In other words, what PI captures is not simply better own-stock prediction than an ML model could, in principle, uncover; it is genuinely *cross-stock* prediction operating through economically defined inter-firm links. Consistent with this interpretation, PI also predicts earnings outcomes, and local-projection evidence shows a pattern of gradual return adjustment without subsequent reversal, which is difficult to

Table 12
Characteristics and categorizations.

Acronym	Characteristic name	Category
age	Firm age	Low_Leverage
aliq_at	Liquidity of book assets	Investment
aliq_mat	Liquidity of market assets	Low_Leverage
ami_126d	Amihud Measure	Size
at_be	Book leverage	Low_Leverage
at_gr1	Asset Growth	Investment
at_me	Assets-to-market	Value
at_turnover	Capital turnover	Quality
be_gr1a	Change in common equity	Investment
be_me	Book-to-market equity	Value
beta_60m	Market Beta	Low_Risk
beta_dimson_21d	Dimson beta	Low_Risk
betadown_252d	Downside beta	Low_Risk
bev_mev	Book-to-market enterprise value	Value
bidaskhl_21d	High–low bid–ask spread	Low_Leverage
capx_gr1	CAPEX growth (1 yr)	Investment
capx_gr2	CAPEX growth (2 yrs)	Investment
capx_gr3	CAPEX growth (3 yrs)	Investment
cash_at	Cash-to-assets	Low_Leverage
chcsho_12m	Net stock issues	Value
coa_gr1a	Change in current operating assets	Investment
col_gr1a	Change in current operating liabilities	Investment
coskew_21d	Coskewness (21 d)	Seasonality
cowc_gr1a	Change in current operating working capital	Accruals
cop_at	Cash-based operating profits-to-book assets	Quality
cop_atl1	Cash-based operating profits-to-lagged book assets	Quality
dgp_dsale	Change gross margin minus change sales	Quality
dbnetis_at	Debt-net issues-to-assets	Seasonality
debt_gr3	Growth in book debt (3 yrs)	Debt_Issuance
debt_me	Book debt-to-market equity	Value
div12m_me	Dividend yield	Value
dolvol_126d	Dollar trading volume (126 d)	Size
dolvol_var_126d	CV of dollar trading volume (126 d)	Profitability
dsale_drec	Change sales minus change receivables	Profit_Growth
dsale_dsga	Change sales minus change SG&A	Profit_Growth
ebit_bev	EBIT-to-book enterprise value	Profitability
ebit_sale	EBIT-to-sales	Profitability
ebitda_mev	EBITDA-to-market enterprise value	Value
emp_gr1	Employment growth	Investment
eq_dur	Equity duration	Value
eqnetis_at	Equity-net issues-to-assets	Value
eqnp_12m	Equity net payout (12 m)	Value
eqnp_me	Equity net payout-to-market equity	Value
eqpo_me	Equity purchases-to-market equity	Value
fcf_me	Free cash flow-to-market equity	Value
fnl_gr1a	Change in financial liabilities	Debt_Issuance
f_score	Piotroski F-score	Profitability
gp_at	Gross profits-to-assets	Quality
gp_atl1	Gross profits-to-lagged assets	Quality
inv_gr1	Inventory growth	Investment
inv_gr1a	Change in inventory	Investment
iskew_capm_21d	Idiosyncratic skewness (CAPM, 21 d)	Short_Term_Reversal
iskew_ff3_21d	Idiosyncratic skewness (FF3, 21 d)	Short_Term_Reversal
iskew_hxz4_21d	Idiosyncratic skewness (HXZ4, 21 d)	Short_Term_Reversal
ivol_capm_21d	Idiosyncratic volatility (CAPM, 21 d)	Low_Risk
ivol_capm_252d	Idiosyncratic volatility (CAPM, 252 d)	Low_Risk
ivol_ff3_21d	Idiosyncratic volatility (FF3, 21 d)	Low_Risk
ivol_hxz4_21d	Idiosyncratic volatility (HXZ4, 21 d)	Low_Risk
kz_index	Kaplan–Zingales index	Seasonality
lnoa_gr1a	Change in long-term net operating assets	Investment
lti_gr1a	Change in long-term investments	Seasonality
market_equity	Market equity	Size
mispricing_mgmt	Change in net operating assets (mispricing)	Investment
mispricing_perf	Mispricing performance	Quality
ncoa_gr1a	Change in noncurrent operating assets	Investment
ncol_gr1a	Change in noncurrent operating liabilities	Debt_Issuance
netdebt_me	Net debt-to-market equity	Low_Leverage
netis_at	Net issues-to-assets	Value
nfna_gr1a	Change in net financial assets	Debt_Issuance
ni_be	Net income-to-book equity	Profitability
ni_inc8q	Change in quarterly return on income (8 q)	Quality
ni_me	Net income-to-market equity	Value
niq_at	Quarterly net income-to-assets	Quality

(continued on next page)

Table 12 (continued).

niq_at_chg1	Change in quarterly ROA	Profit_Growth
niq_be	Quarterly net income-to-book equity	Profitability
niq_be_chg1	Change in quarterly ROE	Profit_Growth
niq_su	Net income surprise	Profit_Growth
nncoa_gr1a	Change in net noncurrent operating assets	Investment
noa_at	Net operating assets-to-assets	Debt_Issuance
noa_gr1a	Change in net operating assets	Investment
ocf_at	Operating cash flow-to-assets	Profitability
ocf_at_chg1	Change in operating cash flow-to-assets	Profit_Growth
ocf_me	Operating cash flow-to-market equity	Value
ocfq_saleq_std	Std. dev. of quarterly OCF-to-sales	Low_Risk
oaccruals_at	Operating accruals-to-assets	Accruals
oaccruals_ni	Operating accruals-to-net income	Accruals
o_score	Ohlson O-score	Profitability
op_at	Operating profits-to-assets	Quality
op_atl1	Operating profits-to-lagged assets	Quality
ope_be	Cash-based operating profits-to-book equity	Profitability
ope_bel1	Cash-based operating profits-to-lagged book equity	Profitability
opex_at	Operating expenses-to-assets	Quality
ppeinv_gr1a	Change PPE and Inventory	Investment
prc	Price per share	Size
prc_highprc_252d	12-month maximum price ratio	Momentum
qmj_prof	QMJ profitability factor	Quality
qmj_safety	QMJ safety factor	Quality
resff3_6_1	FF3 residual return (6–1 m)	Momentum
resff3_12_1	FF3 residual return (12–1 m)	Momentum
ret_1_0	1-month reversal return	Short_Term_Reversal
ret_3_1	3–1-month momentum return	Momentum
ret_6_1	6–1-month momentum return	Momentum
ret_9_1	9–1-month momentum return	Momentum
ret_12_1	12–1-month momentum return	Momentum
ret_12_7	12–7-month return	Profit_Growth
rmax1_21d	1-day maximum return (21 d)	Low_Risk
rmax5_21d	5-day maximum return (21 d)	Low_Risk
rmax5_rvol_21d	Max-return-to-volatility ratio (21 d)	Short_Term_Reversal
rskew_21d	Return skewness (21 d)	Short_Term_Reversal
rvol_21d	Return volatility (21 d)	Low_Risk
sale_bev	Sales-to-book enterprise value	Quality
sale_emp_gr1	Sales-per-employee growth	Profit_Growth
sale_gr1	Sales growth (1 yr)	Investment
sale_gr3	Sales growth (3 yrs)	Investment
sale_me	Sales-to-market equity	Value
saleq_gr1	Sales growth (1 q)	Investment
saleq_su	Sales surprise	Profit_Growth
seas_1_1an	Annual seasonal return	Profit_Growth
seas_1_1na	NA seasonal return	Momentum
sti_gr1a	Change in short-term investments	Seasonality
taccruals_at	Total accruals-to-assets	Accruals
taccruals_ni	Total accruals-to-net income	Accruals
tangibility	Asset tangibility	Low_Leverage
tax_gr1a	Change in tax expenses	Profit_Growth
turnover_126d	Share turnover (126 d)	Low_Risk
turnover_var_126d	CV of turnover (126 d)	Profitability
z_score	Altman Z-score	Low_Leverage
zero_trades_21d	Zero-volume days (21 d)	Low_Risk
zero_trades_126d	Zero-volume days (126 d)	Low_Risk
zero_trades_252d	Zero-volume days (252 d)	Low_Risk

This table lists all the 130 firm-specific characteristics we study in this paper. For the source of each characteristic, please see [Jensen et al. \(2023\)](#). The firm-specific characteristics are classified into 13 groups: Accruals, Debt_Issuance, Investment, Low_Leverage, Low_Risk, Momentum, Profit_Growth, Profitability, Quality, Seasonality, Short_Term_Reversal, Size, and Value.

reconcile with pure risk-based explanations and instead supports an information-diffusion/underreaction view.

The developed framework is flexible along two dimensions. First, it accommodates both symmetric peer structures (such as industries) and inherently asymmetric ones (such as supply-chain networks), which allows us to study the role of asymmetry in cross-stock predictability. Second, the economically grounded network can be embedded within richer statistical environments—for example as the center of a Bayesian prior or within combinations of multiple plausible networks. These features position PI as a transparent baseline for future work that blends economic structure with data-driven network learning.

Overall, the evidence shows that once economically motivated inter-firm linkages are made explicit, they account for a meaningful share

of return and earnings predictability that survives modern ML benchmarks and operates through *cross-stock* rather than purely own-stock information.

CRediT authorship contribution statement

Doron Avramov: Writing – original draft, Writing – review & editing, Project administration, Methodology, Formal analysis, Conceptualization. **Shuyi Ge:** Writing – original draft, Writing – review & editing, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Visualization, Conceptualization. **Shaoran Li:** Writing – original draft, Writing – review & editing, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Table 13
Descriptive statistics—raw values.

Variable	Observations (in 000's)	Mean	Standard deviation	Correlation with PI
(1) Accruals				
Change in current operating working capital(cowc_gr1a)	2394768	0.004	0.186	−0.066
Operating accruals(oaccruals_at)	2568257	−0.053	0.377	−0.045
Percent operating accruals(oaccruals_ni)	2566614	−1.647	44.739	−0.018
Total accruals(taccruals_at)	2540945	−0.061	0.473	0.001
Percent total accruals(taccruals_ni)	2538887	−3.225	81.831	0.006
(2) Debt_Issuance				
Growth in book debt (3 years)(debt_gr3)	2039953	17.753	438.973	−0.014
Change in financial liabilities(fnl_gr1a)	2685962	0.012	0.287	−0.063
Change in noncurrent operating liabilities(ncol_gr1a)	2420052	0.003	0.105	−0.004
Change in net financial assets(nfna_gr1a)	2685962	−0.009	0.304	0.052
Net operating assets(noa_at)	2396636	1.311	33.504	−0.009
(3) Investment				
Liquidity of book assets(aliqu_at)	2423731	1.518	29.948	−0.010
Asset Growth(at_gr1)	2691394	1.246	44.363	−0.010
Change in common equity(be_gr1a)	2538328	0.020	0.259	−0.085
CAPEX growth (1 year)(capx_gr1)	2425229	1.756	38.721	−0.018
CAPEX growth (2 years)(capx_gr2)	2247680	4.013	101.770	−0.017
CAPEX growth (3 years)(capx_gr3)	2071885	5.322	122.147	−0.017
Change in current operating assets(coa_gr1a)	2418001	0.019	0.188	−0.084
Change in current operating liabilities(col_gr1a)	2428113	0.014	0.151	−0.028
Hiring rate(emp_gr1)	2279786	0.062	0.313	−0.118
Inventory growth(inv_gr1)	2035779	0.665	13.097	−0.019
Inventory change(inv_gr1a)	2641962	0.006	0.080	−0.093
Change in long-term net operating assets(lnoa_gr1a)	2312163	0.028	0.120	−0.142
Mispricing factor: Management(mispricing_mgmt)	2680207	0.499	0.183	0.246
Change in noncurrent operating assets(ncoa_gr1a)	2418991	0.029	0.298	−0.098
Change in net noncurrent operating assets(nncoa_gr1a)	2387718	0.025	0.306	−0.095
Change in net operating assets(noa_gr1a)	2386445	0.809	33.785	−0.009
Change PPE and Inventory(ppeinv_gr1a)	2363836	0.157	3.325	−0.024
Sales Growth (1 year)(sale_gr1)	2587505	0.653	15.245	−0.019
Sales Growth (3 years)(sale_gr3)	2228502	3.630	105.998	−0.010
Sales growth (1 quarter)(saleq_gr1)	2558116	0.819	19.837	−0.013
(4) Low_Leverage				
Firm age(age)	2980487	212.785	190.960	0.057
Liquidity of market assets(aliqu_mat)	2252927	0.494	0.330	0.136
Book leverage(at_be)	2708629	5.111	38.977	−0.021
The high-low bid-ask spread(bidaskhl_21d)	2671495	0.020	0.036	−0.009
Cash-to-assets(cash_at)	2797093	0.180	0.227	0.016
Net debt-to-price(netdebt_me)	2795312	0.676	4.888	−0.014
Asset tangibility(tangibility)	2446681	0.649	0.235	0.076
Altman Z-score(z_score)	2406981	6.398	42.079	−0.037
(5) Low_Risk				
Market Beta(beta_60m)	2220915	1.122	0.758	−0.009
Dimson beta(beta_dimson_21d)	2616482	0.889	2.507	−0.024
Downside beta(betadown_252d)	2546391	0.924	0.894	−0.059
Idiosyncratic volatility from the CAPM (21 days)(ivol_capm_21d)	2616482	0.033	0.031	−0.111
Idiosyncratic volatility from the CAPM (252 days)(ivol_capm_252d)	2578926	0.036	0.027	−0.086
Idiosyncratic volatility from the Fama-French 3-factor model(ivol_ff3_21d)	2616482	0.032	0.031	−0.106
Idiosyncratic volatility from the q-factor model(ivol_hxz4_21d)	2616482	0.032	0.031	−0.106
Cash flow volatility(ocfq_saleq_std)	2021187	5.339	81.857	−0.026
Maximum daily return(rmax1_21d)	2616482	0.082	0.104	−0.136
Highest 5 days of return(rmax5_21d)	2616482	0.046	0.044	−0.167
Return volatility(rvol_21d)	2616482	0.035	0.032	−0.115
Share turnover(turnover_126d)	2820802	0.006	0.026	−0.050
Number of zero trades ... (1 month)(zero_trades_21d)	2870711	1.484	3.657	0.054
Number of zero trades ... (6 months)(zero_trades_126d)	2820802	1.467	3.436	0.070
Number of zero trades ... (12 months)(zero_trades_252d)	2753339	1.449	3.350	0.073
(6) Momentum				
Current price to high price over last year(prc_highprc_252d)	2577361	0.734	0.231	0.093
Residual momentum t-6 to t-1(resff3_6_1)	2422411	−0.072	0.648	0.084
Residual momentum t-12 to t-1(resff3_12_1)	2425026	−0.029	0.285	0.231
Price momentum t-3 to t-1(ret_3_1)	2930213	0.021	0.267	0.017
Price momentum t-6 to t-1(ret_6_1)	2867342	0.053	0.450	0.058
Price momentum t-9 to t-1(ret_9_1)	2804836	0.088	0.599	0.098
Price momentum t-12 to t-1(ret_12_1)	2742959	0.128	0.747	0.112
Year 1-lagged return, non-annual(seas_1_1na)	2704009	0.011	0.055	0.023

(continued on next page)

Table 13 (continued).

(7) Profit_Growth				
Change sales minus change receivables(dsale_drec)	2347352	−0.180	14.578	0.006
Change sales minus change SG&A(dsale_dsga)	2013334	0.125	3.832	−0.014
Change in quarterly return on assets(niq_at_chg1)	2461044	0.007	0.470	0.004
Change in quarterly return on equity(niq_be_chg1)	2331291	−0.023	2.049	0.011
Standardized earnings surprise(niq_su)	2256233	−0.183	3.096	0.096
Change in operating cash flow to assets(ocf_at_chg1)	2607088	0.008	0.454	0.015
Price momentum t-12 to t-7(ret_12_7)	2736461	0.057	0.443	0.097
Labor force efficiency(sale_emp_gr1)	2341645	0.396	8.629	−0.014
Standardized revenue surprise(saleq_su)	2212543	0.164	2.838	0.044
Year 1-lagged return, annual(seas_1_lan)	2713456	0.012	0.178	0.089
Tax expense surprise(tax_gr1a)	2653815	0.002	0.042	0.031
(8) Profitability				
Coefficient of variation for dollar trading volume(dolvol_var_126d)	2820732	1.458	1.042	0.024
Return on net operating assets(ebit_bev)	2659302	−0.700	17.905	0.013
Profit margin(ebit_sale)	2719724	−4.239	102.090	0.019
Piotroski F-score(f_score)	2149003	4.778	1.788	0.147
Return on equity(ni_be)	2696790	−0.356	8.276	0.029
Quarterly return on equity(niq_be)	2559057	−0.049	1.629	0.035
Ohlson O-score(o_score)	2357260	−1.908	6.094	−0.074
Operating cash flow to assets(ocf_at)	2744827	−0.020	0.357	0.125
Operating profits-to-book equity(ope_be)	2301662	−0.066	6.225	0.033
Operating profits-to-lagged book equity(ope_bel1)	2192465	0.042	7.541	0.024
Coefficient of variation for share turnover(turnover_var_126d)	2820738	1.427	1.017	0.033
(9) Quality				
Capital turnover(at_turnover)	2760086	0.991	0.945	0.049
Cash-based operating profits-to-book assets(cop_at)	2566079	0.124	0.365	0.144
Cash-based operating profits-to-lagged book assets(cop_atl1)	2537857	0.003	9.764	0.010
Change gross margin minus change sales(dgp_dsale)	2282887	0.005	8.787	0.014
Gross profits-to-assets(gp_at)	2785344	0.276	0.360	0.109
Gross profits-to-lagged assets(gp_atl1)	2682928	0.339	0.970	0.020
Mispricing factor: Performance(mispricing_perf)	2906714	0.496	0.213	0.217
Number of consecutive quarters with earnings increases(ni_inc8q)	2103334	2.735	3.112	0.031
Quarterly return on assets(niq_at)	2660465	−0.016	0.197	0.082
Operating profits-to-book assets(op_at)	2786120	0.067	0.292	0.122
Operating profits-to-lagged book assets(op_atl1)	2683679	0.056	1.618	0.039
Operating leverage(opex_at)	2785477	0.937	0.943	0.036
Quality minus Junk: Profitability(qmj_prof)	2775068	0.002	1.000	0.183
Quality minus Junk: Safety(qmj_safety)	2814590	0.000	0.997	0.094
Assets turnover(sale_bev)	2659462	3.111	25.085	0.016
(10) Seasonality				
Coskewness(coskew_21d)	2616482	−0.014	0.315	−0.011
Net debt issuance(dbnets_at)	2772222	−0.037	0.299	−0.022
Kaplan–Zingales index(kz_index)	2424265	−30.214	597.785	0.007
Change in long-term investments(lti_gr1a)	2488809	0.004	0.077	−0.022
Change in short-term investments(sti_gr1a)	2448288	0.003	0.128	−0.030
(11) Short_Term_Reversal				
Idiosyncratic skewness from the CAPM(iskew_capm_21d)	2616482	0.242	0.947	−0.128
Idiosyncratic skewness from the Fama–French 3-factor model(iskew_ff3_21d)	2616482	0.201	0.860	−0.103
Idiosyncratic skewness from the q-factor model(iskew_hxz4_21d)	2616482	0.182	0.814	−0.098
Short-term reversal(ret_1_0)	2953743	0.010	0.190	−0.235
Highest 5 days of return scaled by volatility(rmax5_rvol_21d)	2479523	1.218	0.539	−0.210
Total skewness(rskew_21d)	2616482	0.242	0.951	−0.143
(12) Size				
Amihud Measure(ami_126d)	2605890	7.837	66.724	0.005
Dollar trading volume(dolvol_126d)	2820796	19410405.633	134964837.005	−0.011
Market equity(characteristic)(market_equity)	2976197	2759.602	18394.302	0.003
Price per share in dollars(prc)	2976197	30.178	707.910	−0.002
(13) Value				
Assets-to-market(at_me)	2800937	3.484	14.484	0.016
Book-to-market equity(be_me)	2706306	0.836	1.457	0.087
Book-to-market enterprise value(bev_mev)	2638084	0.814	3.096	0.059
Net stock issues(chcsho_12m)	2728645	0.160	2.458	−0.032
Debt-to-market(debt_me)	2795312	1.004	5.470	0.000
Dividend yield(div12m_me)	2763825	0.013	0.052	0.041
Ebitda-to-market enterprise value(ebitda_mev)	2725915	0.009	2.117	−0.003
Equity duration(eq_dur)	2331957	17.696	37.033	−0.015
Net equity issuance(eqnetis_at)	2641812	0.075	0.271	−0.152
Equity net payout(eqnp_12m)	2712461	−0.048	0.260	0.128
Net payout yield(eqnp_12m)	2634247	−0.043	0.411	0.041
Payout yield(eqpo_me)	2483779	0.035	0.156	0.031

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Table 13 (continued).

Free cash flow-to-price(fcf_me)	2616 751	−0.112	1.067	0.035
Net total issuance(netis_at)	2641 485	0.035	0.432	−0.110
Earnings-to-price(ni_me)	2789 808	−0.149	1.618	−0.011
Operating cash flow-to-market(ocf_me)	2742 194	0.011	0.906	0.042
Sales-to-market(sale_me)	2783 446	2.147	6.440	0.051
Index				
Peer Index(PI)	2,557,030	0.000	0.289	1.000

The table displays descriptive statistics for firm characteristics defined in Table 12 and the new PI index. The sample spans the period January 1980 through Dec 2024. Means, standard deviations, and correlations are based on the original (unstandardized) variables. To mitigate the influence of outliers, we winsorize the data at the 0.01% and 99.99% levels when computing means and standard deviations. However, our main empirical analysis — following the data filtering procedures of Didisheim et al. (2024) and Kelly et al. (2025) — does not apply winsorization.

Table 14

Descriptive statistics for the peer average characteristics (characteristic name_peer) and The deviation variables (characteristic name_dev) used to construct PI.

Peer variable	Avg Coef	Deviation variable	Avg Coef
zero_trades_21d_peer	−0.471	zero_trades_21d_dev	−1.213
zero_trades_126d_peer	0.419	ret_1_0_dev	−0.744
ret_1_0_peer	0.353	at_me_dev	0.614
ret_12_1_peer	−0.326	zero_trades_126d_dev	0.518
mispricing_perf_peer	0.302	turnover_126d_dev	−0.406
sale_me_peer	0.286	zero_trades_252d_dev	0.38
eqnp_12m_peer	−0.285	be_me_dev	0.365
netis_at_peer	0.28	prc_highprc_252d_dev	0.35
at_turnover_peer	−0.28	aliq_mat_dev	−0.313
seas_1_1na_peer	0.279	o_score_dev	0.311
prc_highprc_252d_peer	0.273	rmax5_21d_dev	0.308
bidaskhl_21d_peer	0.255	rmax5_rvol_21d_dev	−0.301
ivol_capm_21d_peer	−0.244	netdebt_me_dev	−0.256
bev_mev_peer	0.239	ivol_capm_21d_dev	−0.243
rmax1_21d_peer	−0.233	niq_be_dev	0.243
be_me_peer	0.217	op_atl1_dev	0.238
qmj_safety_peer	−0.215	opex_at_dev	0.238
op_atl1_peer	0.199	at_be_dev	−0.233
ret_12_7_peer	0.186	bev_mev_dev	0.231
chcsho_12m_peer	−0.174	op_at_dev	0.23
ami_126d_peer	0.17	qmj_prof_dev	0.223
at_gr1_peer	−0.17	ret_3_1_dev	−0.223
ebit_sale_peer	−0.168	ret_12_1_dev	0.221
ivol_capm_252d_peer	−0.168	be_gr1a_dev	−0.219
cash_at_peer	0.167	turnover_var_126d_dev	0.218
ret_6_1_peer	−0.159	ocf_at_dev	−0.189
ret_9_1_peer	0.159	noa_at_dev	−0.189
cop_at_peer	0.155	at_turnover_dev	−0.179
div12m_me_peer	0.151	dolvol_var_126d_dev	−0.176
dolvol_var_126d_peer	0.148	gp_atl1_dev	−0.175
taccruals_ni_peer	0.139	mispricing_perf_dev	0.172
sale_gr3_peer	0.139	prc_dev	−0.169
seas_1_1an_peer	0.134	saleq_gr1_dev	0.166
gp_atl1_peer	−0.133	ret_9_1_dev	0.164
taccruals_at_peer	−0.133	seas_1_1na_dev	−0.162
iskew_capm_21d_peer	−0.13	ami_126d_dev	−0.159
ni_me_peer	−0.129	gp_at_dev	0.155
betadown_252d_peer	0.128	ocf_me_dev	0.137
noa_at_peer	−0.126	cash_at_dev	0.129
ope_be_peer	−0.124	ebitda_mev_dev	−0.125
turnover_var_126d_peer	−0.119	sale_gr1_dev	−0.118
ope_bell_peer	0.117	seas_1_1an_dev	0.117
noa_gr1a_peer	0.112	niq_at_chg1_dev	0.115
resff3_12_1_peer	0.11	ebit_bev_dev	−0.114
debt_me_peer	−0.109	tangibility_dev	0.112
cop_atl1_peer	−0.108	rvol_21d_dev	−0.104
gp_at_peer	0.105	ivol_capm_252d_dev	−0.101
iskew_hxz4_21d_peer	0.103	coa_gr1a_dev	−0.1
rmax5_rvol_21d_peer	0.098	beta_60m_dev	0.1
aliq_mat_peer	−0.098	oaccruals_at_dev	−0.099
eq_dur_peer	0.098	mispricing_mgmt_dev	−0.098
o_score_peer	0.096	debt_me_dev	−0.098
niq_be_chg1_peer	0.095	iskew_ff3_21d_dev	0.094
ncoa_gr1a_peer	0.094	market_equity_dev	−0.094

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Table 14 (continued).

niq_be_peer	0.092	sale_me_dev	0.093
debt_gr3_peer	−0.092	at_gr1_dev	0.091
ebit_bev_peer	0.091	ppeinv_gr1a_dev	−0.088
capx_gr3_peer	0.09	ret_6_1_dev	−0.087
qmj_prof_peer	0.086	taccruals_ni_dev	0.082
dbnetis_at_peer	−0.084	ebit_sale_dev	0.081
rvol_21d_peer	−0.082	saleq_su_dev	0.077
beta_60m_peer	−0.082	sale_gr3_dev	0.077
nncoa_gr1a_peer	−0.081	noa_gr1a_dev	0.075
fcf_me_peer	0.076	z_score_dev	−0.073
age_peer	0.074	cop_atl1_dev	0.072
rmax5_21d_peer	0.073	ncol_gr1a_dev	0.072
op_at_peer	−0.07	resff3_12_1_dev	0.067
saleq_su_peer	−0.07	dgp_dsale_dev	0.065
capx_gr2_peer	−0.069	ret_12_7_dev	0.06
prc_peer	−0.069	eqpo_me_dev	−0.06
niq_at_chg1_peer	−0.066	ope_bell1_dev	0.058
coskew_21d_peer	−0.066	dsale_dsga_dev	0.058
mispricing_mgmt_peer	0.064	beta_dimson_21d_dev	0.052
ocf_at_chg1_peer	−0.064	eq_dur_dev	0.052
niq_su_peer	−0.057	col_gr1a_dev	0.052
saleq_gr1_peer	0.055	sale_bev_dev	0.051
sale_bev_peer	−0.05	ncoa_gr1a_dev	−0.051
nfna_gr1a_peer	−0.049	debt_gr3_dev	−0.05
at_be_peer	0.048	inv_gr1a_dev	−0.05
sale_gr1_peer	0.048	bidaskhl_21d_dev	0.05
dsale_drec_peer	−0.047	capx_gr1_dev	−0.049
be_gr1a_peer	−0.046	age_dev	−0.048
ni_inc8q_peer	−0.046	rmax1_21d_dev	−0.045
at_me_peer	−0.044	ni_me_dev	−0.045
beta_dimson_21d_peer	−0.042	oaccruals_ni_dev	0.043
ebitda_mev_peer	−0.042	resff3_6_1_dev	−0.042
inv_gr1_peer	−0.041	aliq_at_dev	0.042
eqnetis_at_peer	0.04	dsale_drec_dev	−0.041
market_equity_peer	0.039	eqnetis_at_dev	−0.04
opex_at_peer	−0.038	qmj_safety_dev	−0.038
inv_gr1a_peer	−0.038	emp_gr1_dev	0.038
z_score_peer	0.035	lti_gr1a_dev	−0.037
capx_gr1_peer	−0.034	sti_gr1a_dev	−0.036
ocf_at_peer	0.032	iskew_hxz4_21d_dev	0.036
ret_3_1_peer	−0.032	dbnetis_at_dev	0.034
dgp_dsale_peer	0.032	capx_gr2_dev	−0.034
ni_be_peer	0.028	div12m_me_dev	0.03
col_gr1a_peer	−0.027	ivol_hxz4_21d_dev	−0.029
niq_at_peer	−0.026	eqnp_12m_dev	0.029
ivol_ff3_21d_peer	−0.026	ivol_ff3_21d_dev	−0.028
ocfq_saleq_std_peer	0.025	tax_gr1a_dev	−0.027
oaccruals_at_peer	0.025	niq_be_chg1_dev	−0.027
resff3_6_1_peer	0.025	chcsho_12m_dev	−0.024
cowc_gr1a_peer	0.024	cowc_gr1a_dev	−0.024
f_score_peer	−0.023	coskew_21d_dev	0.023
ocf_me_peer	0.02	ocfq_saleq_std_dev	0.023
aliq_at_peer	0.018	sale_emp_gr1_dev	0.021
sti_gr1a_peer	−0.018	niq_su_dev	−0.021
zero_trades_252d_peer	0.016	fcf_me_dev	0.02
emp_gr1_peer	0.015	nncoa_gr1a_dev	0.019
dolvol_126d_peer	−0.013	fml_gr1a_dev	−0.019
sale_emp_gr1_peer	0.012	taccruals_at_dev	−0.018
tax_gr1a_peer	−0.011	dolvol_126d_dev	0.016

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Table 14 (continued).

eqpo_me_peer	0.011	inv_gr1_dev	0.016
dsale_dsga_peer	0.01	ope_be_dev	0.016
tangibility_peer	0.009	iskew_capm_21d_dev	0.015
coa_gr1a_peer	0.009	kz_index_dev	−0.015
ivol_hxz4_21d_peer	0.008	rskew_21d_dev	−0.015
eqnpo_me_peer	−0.008	betadown_252d_dev	0.014
ncol_gr1a_peer	−0.008	netis_at_dev	−0.013
kz_index_peer	−0.008	ni_be_dev	0.013
turnover_126d_peer	0.008	f_score_dev	−0.013
iskew_ff3_21d_peer	−0.006	ni_inc8q_dev	−0.01
lnoa_gr1a_peer	−0.006	cop_at_dev	0.006
netdebt_me_peer	−0.005	niq_at_dev	0.005
fnl_gr1a_peer	0.004	capx_gr3_dev	0.005
ppeinv_gr1a_peer	−0.003	nfna_gr1a_dev	−0.004
lti_gr1a_peer	−0.002	ocf_at_chg1_dev	−0.002
rskew_21d_peer	−0.002	lnoa_gr1a_dev	−0.002
oaccruals_ni_peer	−0.002	eqnpo_me_dev	−0.002

The variables are presented in descending order by the magnitude of average coefficients in all the estimation windows. The column “Avg Coef” presents the average coefficient*100 for each variable.

Table 15

Do relevant ETFs explain PI abnormal returns?.

	Excess ret	Alpha	Quality	Value	Momentum
Top-minus-bottom portfolio	0.92*** (6.13)				
		0.63** (2.21)	−0.24*** (−3.75)		
		0.51** (2.49)		−0.14*** (−3.27)	
		0.60** (2.09)			−0.20*** (−3.22)
		0.70** (2.51)	−0.82*** (−3.92)	0.56*** (3.51)	0.08 (0.65)

This table reports the loading coefficients and alphas obtained from regressing monthly value-weighted top-minus-bottom PI portfolio returns on BlackRock's iShares MSCI USA Quality Factor ETF (Quality), iShares S&P 500 Value ETF (Value), and iShares MSCI USA Momentum Factor ETF (Momentum). Monthly returns of Quality, Value, and Momentum are available from August 2013, June 2000, and June 2013, respectively. The sample period ends in Dec 2024. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 16

Sentiment effect and PI.

Dependent variable	Observations	Stock sentiment	Industry sentiment	PI
R_{t+1}	1,032,059	0.66 (1.12)		
R_{t+1}	1,032,059		−0.21 (−0.57)	
R_{t+1}	1,032,059	0.71 (1.11)	−0.42 (−1.06)	0.53*** (3.10)

This table shows the average slopes*100; *t*-statistics with Newey–West adjustments of 12 lags from a set of monthly value-weighted Fama–MacBeth regressions. The stock sentiment and industry sentiment variables represent the stock-level sentiment index and industry-level sentiment index, respectively, constructed using RavenPack News Analytics. Control variables include size and book-to-market ratio. Our sample period starts from January 2000 when the news dataset became available. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Oliver Linton: Writing – original draft,, Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

All authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables 12–16.

Data availability

dual peer effect dataset (Original data) (Mendeley Data)

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