Do Trades and Holdings of Market Participants Contain Information About Stocks? A Machine-Learning Approach

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Abstract

We use machine learning to capture nonlinearities and interactions in the relation between trades and holdings of multiple market participants and future stock returns. Our predictor yields a long-short portfolio with significant out-of-sample alpha, forecasts firm fundamentals, and assigns stocks on the right side of most anomalies. Predictability is stronger for smaller or illiquid stocks and stocks with lower analyst coverage or higher idiosyncratic volatility. A factor model based on our predictor achieves higher Sharpe ratio than existing models. Our findings suggest that incorporating nonlinear interactions between trades and holdings of various participants reveals valuable information for price discovery.

`JEL classification:` G10, G11, G23.
`Keywords:` Return predictability; Machine learning; Nonlinearities and interactions; Institutional investors; Trades and holdings; Anomalies.

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1 Introduction

If market participants posses value-relevant information about stocks, a signal that combines their collective trades and holdings should predict future stock returns. Although there is an extensive literature on the informativeness of the trades and holdings of various market participants, most studies focus on one particular type of investor, such as mutual funds, hedge funds, short sellers, or the firms themselves.[1] Several papers also study the role of interactions between pairs of investors—through learning or competition—in the informational content of their trades.[2] However, these interactions may extend beyond pairs of investors. Also, different investors may hold various types of information and be informed at different times. Even the trades of investors who make systematically poor bets can reveal information about future stock returns. In this paper, we examine the combined informational role of multiple types of market participants. Specifically, we use machine learning to construct a return predictor that aggregates the information in the trades and holdings of various market participants and assess its ability to predict stock returns out of sample.

Like McLean et al. (2022), we consider nine market participants, including six types of institutional investors (mutual funds, hedge funds, banks, insurance companies, wealth management firms, and other institutions) as well as firms, short sellers, and retail investors. We aggregate trade and holdings by type of market participant so that we can identify the effect of interactions between different types of investors. This also facilitates the comparison of our results with those in the literature on the informational content of market participant trades. Moreover, following Gompers and Metrick (2001) and Yan and Zhang (2009), we decompose current quarterly holdings into lagged quarterly holdings plus current quarterly trades. If a specific type of market participant is informed about a change in the expected return of a stock,

[1] For studies on the relation between mutual fund *holdings* and performance see, for example, Daniel et al. (1997) and Wermers (2000), and for studies focusing on the *trades* of specific types of investors see, for instance, Diether et al. (2009), Aggarwal and Jorion (2010), Boehmer et al. (2010), Baker et al. (2010), Kaniel et al. (2012), Kelley and Tetlock (2013), Cao et al. (2018), and Boehmer et al. (2021). McLean et al. (2022) conduct a comprehensive analysis on the trades of nine market participants and their relation with return predictability and anomalies, by focusing on the individual effect of each type of participant.

[2] For example, Sias and Whidbee (2010) study interactions between insiders and institutional investors, Massa et al. (2015) between insiders and shortsellers, and Jiao et al. (2016) between shortsellers and the long positions of hedge funds.

its current quarterly trade in that stock should strongly predict future returns. Conversely, to the extent that lagged holdings proxy for current holdings, the predictability of lagged holdings could reflect the effect of persistent demand on future stock returns. Persistent holdings might also reflect information about the stock long-term performance.

To construct the return predictor, we use several nonlinear machine-learning methods that can capture nonlinearities and interactions in the relation between the trades and holdings of multiple market participants and future stock returns. Specifically, we use random forest, gradient boosting regression trees, and artificial neural networks.[3] For comparison, we also employ six linear models: ordinary least squares plus five linear machine-learning methods, including principal component regression, partial least squares, adaptive least absolute shrinkage and selection operator, ridge regression, and elastic net. These linear machine-learning methods have been recently used in asset pricing (Chinco et al., 2019; Gu et al., 2020; Dong et al., 2022; Leippold et al., 2022) and can mitigate the overfitting caused by collinearity among predictors.

We use a rolling-window approach to evaluate the out-of-sample performance of the linear and nonlinear predictors. For each model and five-year estimation window, we use stock-month panel data, including both trades and lagged holdings of the nine market participants, to predict next-month returns. Then, for each stock we average the predicted returns across the six linear models to construct a linear composite predictor (LCP) and across the nonlinear models to construct a nonlinear composite predictor (NLCP). Each month, we sort our sample of stocks into decile portfolios based on the LCP or NLCP, construct equal-weighted long-short portfolios that buy the high and short the low decile, and evaluate their out-of-sample monthly alphas with respect to the five Fama and French (2015) factors plus the momentum factor (FF5+MOM) and the five Hou et al. (2021) factors plus the momentum factor (q5+MOM).

Although our work focuses on the information in the combined trades of multiple market participants, as a benchmark we also evaluate the performance of the univariate decile portfolios constructed by sorting stocks based on the trades (or holdings) of a single type of investor.

[3]The literature has documented the presence of nonlinear relations between predictors and future asset returns (Kelly et al., 2019; Gu et al., 2020; Bianchi et al., 2021; Binsbergen et al., 2022; Leippold et al., 2022). Given the complex interactions among multiple types of market participants, it is reasonable to expect similar nonlinear relations between the trades and holdings of different market participants and future stock returns.

We find that the univariate long-short portfolios obtained from the trades of several types of investors have significant alphas. For instance, while the long-short portfolios based on the trades of hedge funds, other institutions, or retail traders have significantly positive alpha, those based on the trades of banks or mutual funds have significantly negative alpha. We also find that the only univariate long-short portfolio based on holdings that achieves a significant alpha is based on short seller holdings, consistent with the literature that documents the informational content of short interest (Desai et al., 2002; Asquith et al., 2005; Diether et al., 2009; Karpoff and Lou, 2010; Boehmer et al., 2010).

The results for the linear composite predictor (LCP) show that there are benefits from linearly combining the information in the trades and holdings of multiple market participants. In particular, we find that a long-short portfolio obtained by buying the high and shorting the low decile portfolio of stocks sorted by the LCP has significant monthly alphas of 1.78% and 1.68% with respect to the FF5+MOM and q5+MOM models. Moreover, these long-short portfolio alphas are driven by both the long and short legs, each with significant but oppositely signed alphas. The long-short alphas are also significantly higher than those of the univariate long-short portfolios, with the exception of the portfolio based on short seller holdings, for which although the alpha of the LCP long-short portfolio is more than 10% higher, the difference is not significant.

The results for the nonlinear composite predictor (NLCP) reveal even more significant gains from capturing nonlinearities and interactions in the relation between the trades and holdings of multiple market participants and future stock returns. For instance, the long-short portfolio of stocks based on the NLCP has alphas of 2.74% and 2.60% with respect to the FF5+MOM and q5+MOM models, which are 96 and 92 basis points higher than those of the long-short portfolio based on the LCP, with the differences being significant at the 1% level. The NLCP long-short portfolio significantly outperforms also the univariate long-short portfolios, including that based on short seller holdings. Figure 1 illustrates the performance of the univariate, LCP, and NLCP long-short portfolios.

[Insert Figure 1 here]

We find that the NLCP long-short portfolios continue to generate significantly positive alpha for up to 16 months after portfolio formation. This suggests that the return predictability is not driven by price pressure and that there is information about stocks in the collective trades and holdings of market participants. The performance of the NLCP long-short portfolio is robust to considering transaction costs of 60 basis points. Fama-Macbeth regressions show that the positive relation between next-month returns and the NLCP remains statistically significant after controlling for common firm characteristics. The effect in Fama-MacBeth regressions is also economically significant, with a spread between the expected monthly return of stocks in the high and low NLCP deciles of 1.54%.

To assess the relative significance of trades and holdings for the composite predictors, we construct versions of the LCP and NLCP based on only trades or only holdings. When we include these predictors individually in Fama-MacBeth regressions, we find that both trading- and holdings-based LCPs and NLCPs significantly predict future stock returns. However, when we include all predictors in a single Fama-MacBeth regression, only the NLCPs remain significant. Specifically, the time-series mean coefficient estimate for the trading-based NLCP is 0.32, significant at the 5% level and that for the holdings-based NLCP is 0.46, significant at the 1% level. In contrast, the coefficients for the trading-based and holdings-based LCPs are not significant after controlling for the NLCPs based on trades and holdings.

Is the predicting power of the machine-learning models driven by the (nonlinear) interactions among the trades and holdings of all types of market participants, or primarily by a few? To answer this question, we investigate the importance of the different predicting variables and their interactions for the random forest model using the SHAP values of Lundberg and Lee (2017). While certain investors—such as mutual funds, insurance companies, and wealth management firms—are more important, no single type of investors dominates the predictions. Consistent with the Fama-MacBeth regressions, we find that both trades and holdings are important. However, despite the univariate portfolio based on short seller holdings generating a highly significant alpha, short seller holdings is not among the top variables for random forest. This suggests that, when we consider (jointly) the trades and holdings of multiple market participants, the informational content of short seller holdings is subsumed by other predicting variables. Additionally, we find that random forest exploits the interactions

between the lagged holdings of different types of investors as well as between the trades of some investors and the lagged holdings of others.

If the NLCP reflects valuable information that is not yet absorbed by the market, we would expect its ability to predict returns to be stronger for firms with a more uncertain information environment. Consistent with this hypothesis, we find that the predictive power of the NLCP is stronger for stocks with lower market capitalization, higher idiosyncratic volatility, lower liquidity, lower analyst coverage, and higher analyst disagreement, although the effects are similar regardless of firm age. We also find that the benefits of exploiting nonlinearities and interactions, compared to using a linear model, are present only for small and medium stocks.

If the NLCP contains information about stock returns, it may also predict future firm fundamentals. The existing literature provides mixed evidence on whether the trades of various types of market participants predict firm fundamentals (Baker et al., 2010; Boehmer et al., 2020). We find that the NLCP forecasts key fundamentals for the next quarter, including gross margin (GM), return on assets (ROA), return of equity (ROE), and cash flow (CF), even after controlling for recent fundamentals and common firm characteristics. The results for the LCP are qualitatively similar. Given that the NLCP can predict firm fundamentals, it should also predict earnings announcement returns, which capture the combined effect of reported fundamentals on stock returns. Indeed, we find that the spread between the expected earnings announcement return of stocks in the high and low NLCP deciles is 0.56%, significant at the 1% level. The ability of LCP and NLCP to predict future firm fundamentals and earnings announcement returns provides support to the hypothesis that the collective trades and holdings of market participants contain information about stocks.

Prior studies suggest that market participants such as institutional investors trade on the wrong side of anomalies; see, for instance, Hirshleifer et al. (2011), Edelen et al. (2016), Patton and Weller (2020), and McLean et al. (2022). We sort our sample stocks into decile portfolios based on the LCP and NLCP and examine firm-characteristic values of these portfolios with respect to each anomaly, as well as the characteristic spreads between the high and low deciles. Out of the 102 stock return anomalies documented in Green et al. (2017), we select the 12 anomalies whose returns are statistically significant for our sample period. Both the LCP and

NLCP assign stocks on the right side of all the 12 anomalies, except short-term reversal and analyst coverage.

Given that the LCP and NLCP are aligned with most anomalies, it is interesting to examine whether a factor model based on the LCP or NLCP can explain the cross-section of anomaly returns. To do this, we construct an LCP or NLCP factor by taking a long position in the high decile and a short position in the low decile of stocks sorted by the LCP or NLCP. We then form a two-factor model with the market factor and the LCP or NLCP factor. We find that the average absolute alpha for the 12 significant anomalies with respect to the LCP and NLCP factor models is 0.46 and 0.50, with average absolute t-statistics of 1.19 and 1.16, comparable to the FF5+MOM and q5+MOM models. That is, the two-factor model with only the market and our LCP or NLCP factor performs similar to the prominent FF5+MOM and q5+MOM models in terms of its ability to explain anomaly returns. This is a notable result because the LCP and NLCP factors are constructed using only the trades and holdings of market participants, ignoring any anomaly information.

Barillas and Shanken (2018) show (under mild assumptions) that an economically meaningful criterion to compare factor models is the Sharpe ratio generated by their factors. We find that the NLCP factor model produces an annualized Sharpe ratio of 3.09, which is significantly higher than those generated by the FF5+MOM and q5+MOM models (1.13 and 1.71). Thus, the Sharpe ratio results confirm that the NLCP factor model contains information that helps to span the *overall* investment opportunity set better than existing factor models. In other words, the NLCP identifies information important for asset pricing that is not captured by either existing factor models or the set of anomalies we consider.

Our manuscript is closely related to the literature that studies whether market participant trades contain information about future stock returns. Most of the existing literature focuses on a particular type of investors (Diether et al., 2009; Aggarwal and Jorion, 2010; Boehmer et al., 2010; Baker et al., 2010; Kaniel et al., 2012; Kelley and Tetlock, 2013; Cao et al., 2018; Boehmer et al., 2021) or the interactions between pairs of investors (Sias and Whidbee, 2010; Massa et al., 2015; Jiao et al., 2016). Da et al. (2024) find that the net trading by outside arbitrageurs (hedge funds and short sellers) and that by firm insiders both independently predict stock returns, and the two types of investors hold different types of information.

McLean et al. (2022) study the trades of nine market participants and their relation with anomalies and future returns, by focusing on the individual effect of each type of participant. A distinctive feature of our work is that we highlight the importance of considering the trades and holdings of multiple types of investors *jointly* and using machine learning to capture nonlinearities and interactions in their relation to future stock returns.

Our work is also related to the growing literature that uses machine learning in asset pricing and investment. Most of the existing work focuses on using machine learning to study the cross section and time series of stock returns, using firm characteristics (Gu et al., 2020; Kozak et al., 2020; Bryzgalova et al., 2021; Chatigny et al., 2022; Leippold et al., 2022). Several recent papers use machine learning to study mutual-fund performance (Li and Rossi, 2021; DeMiguel et al., 2023; Kaniel et al., 2023). We show that machine learning successfully extracts value-relevant information from the combined trades and holdings of multiple market participants, and the predictor based on these signals strongly predicts future stock returns after controlling for historical returns and firm characteristics.

Koijen and Yogo (2019) develop an equilibrium asset-pricing model based on the asset demand of market participants. They use individual institutional holdings to study the model's implications for asset market movements and volatility. Their research has spurred a growing literature on demand system asset pricing (Egan et al., 2024; Davis et al., 2024; Noh et al., 2024; Huebner, 2024; Da, 2022). Importantly, the asset demands or demand shocks in these models are exogenous components and unrelated to firm fundamentals, with demand elasticity determining contemporaneous equilibrium prices. In contrast, we show that the NLCP, which captures the (nonlinear) interactions of the trades and holdings of multiple market participants, contains information about firm fundamentals and predicts future stock returns. Our work is also related to Gabaix et al. (2024), who apply machine learning to individual institutional holdings in order to extract asset embeddings that contain information relevant to investors. We show that the trades and holdings of various types of investors contain information about future stock returns that is not yet reflected in asset prices. Moreover, we aggregate trade and holdings data at the market-participant type level, which allows us to examine which types of market participants have information about stocks and how they interact in financial markets.

The remainder of this manuscript is organized as follows. Section 2 describes the data, methodology, and descriptive statistics. Section 3 evaluates the performance of the composite return predictors. Section 4 studies how the predictability of the composite predictors varies with the firm's information environment, and explores whether the composite predictors forecast firm fundamentals and earnings announcement returns. Section 5 examines the relation between composite predictors and anomalies and the performance of factor models constructed from these predictors. Section 6 concludes.

2 Data, methodology, and descriptive statistics

This section discusses our data and methodology. Section 2.1 describes the data sources and how we construct the predicting variables for the machine-learning models. Section 2.2 gives an overview of the machine-learning methods we employ. Section 2.3 explains how we evaluate the out-of-sample performance of the linear and nonlinear composite predictors. Finally, Section 2.4 provides descriptive statistics.

2.1 Data sources and predicting variables

The predicting variables we use to train the machine-learning models are the quarterly trades and lagged quarterly holdings of the nine market participants considered by McLean et al. (2022), which include six types of institutional investors (mutual funds, hedge funds, banks, insurance companies, wealth management firms, and other institutions) as well as firms, short sellers, and retail investors.[4] For firms and retail investors, we consider only their trades because we lack relevant information about their holdings. Thus, we have 16 predicting variables, including nine trading and seven holding variables. We use the same methodology as McLean et al. (2022) to construct all of these variables, except for the trades of retail investors, which we construct using the algorithm recently proposed by Barber et al. (2024).[5]

[4]Brian Bushee provides a classification of institutional investors consisent with that of McLean et al. (2022) at https://accounting-faculty.wharton.upenn.edu/bushee/.

[5]McLean et al. (2022) use the same dataset and the algorithm of Boehmer et al. (2021) to construct retail trades. We apply the revised algorithm of Barber et al. (2024) to address concerns about potential misidentification of retail investors (Battalio et al., 2023). While we term the resulting measure "retail investor trades," our findings do not depend solely on its capturing the trades of retail investors. It may also reflect

We obtain institutional holdings data from *Thomson/Refinitiv S12* and *13F* filings to construct the quarterly holdings of the aforementioned six types of institutional investors.[6] We normalize quarterly institutional holdings by dividing them by the total number of shares outstanding. We estimate the trades of institutional investors as the change in their standardized holdings from the previous quarter.

To measure retail trades, we use daily off-exchange marketable orders from the *Trade and Quote* (*TAQ*) dataset. We then apply the algorithm of Barber et al. (2024) to identify individual trades by retail investors and estimate the aggregate retail trades using monthly retail order imbalance.

We calculate short interest ratio as quarter-end short interest from *Compustat*, divided by the number of shares outstanding. Following McLean et al. (2022), we sign the short interest ratio so that higher values correspond to less shorting. We term the signed short interest ratio as short seller holdings to be in line with the other holdings variables. We then estimate short seller trades as the quarterly change in signed short interest ratio.

We estimate firm trades as the difference between quarter-end share repurchases and share issues, divided by the number of outstanding shares. We sign this variable so that decreases (increases) in shares outstanding correspond to positive (negative) values of firm trading. Appendixes A.1 and A.2 provide a detailed description of our predicting variable construction.

To construct our sample from the *CRSP* dataset, we select common stocks (with share codes of 10 or 11) listed on the NYSE, AMEX, or Nasdaq (with exchange codes of 1, 2, or 3) and exclude stocks with prices under $1. We also acquire accounting variables from *Compustat* and analyst forecast and recommendation data from the *Institutional Brokers' Estimate System (I/B/E/S)*. Following the methodology outlined by Green et al. (2017), we

the collective effect of trades by investors, including possibly some institutional investors, who benefit from price discounts in the off-exchange market. Moreover, Table B.3 in Appendix B shows that our findings are robust to excluding retail investor trades from our sample.

[6]Consistent with McLean et al. (2022), we associate holdings data with the date at which the investor held the positions, rather than the date at which they were reported, which could be up to 45 days later. This is because our research question is whether investor trades contain information at the time they are executed. Nevertheless, Table 5 shows that the NLCP portfolios continue producing significantly positive alpha up to 16 months after portfolio formation, which suggests that one could implement profitable investment strategies in real time based on publicly available holdings data.

replicate their 102 stock anomalies. Our sample period spans January 2008 to December 2020.

2.2 Machine-learning methods

We use the quarterly trades and lagged quarterly holdings constructed in Section 2.1 as predicting variables for the linear and nonlinear machine-learning models. We closely follow the approach in existing papers that apply machine learning to stock analysis (Gu et al., 2020; Kozak et al., 2020).

We consider six linear models: *ordinary least squares* (OLS) and five linear machine-learning methods. In particular, we consider the two dimension-reduction methods used by Gu et al. (2020): *principle components regression* (PCR) and *partial least squares* (PLS). We also consider three popular regularization methods described in Hastie et al. (2009): the adaptive version of *least absolute shrinkage and selection operator* (ALasso), *ridge regression* (Ridge), and *elastic net* (ENet).

Gu et al. (2020) show that accounting for nonlinearities and interactions substantially improves the accuracy of return predictive models. Similarly, DeMiguel et al. (2023) find that nonlinear machine-learning models help to select a portfolio of actively managed mutual funds with significant out-of-sample alphas. Following these papers, we consider three sets of nonlinear machine-learning models: *gradient boosted regression trees* (GBRT), *random forest* (RF), and *artificial neural networks* (ANN). GBRT integrates multiway predictor interactions and utilizes a boosting algorithm that recursively combines forecasts from regression trees to enhance performance. Similarly, RF aggregates forecasts from regression trees using a bootstrap aggregation method, which reduces correlation among the regression trees and increases prediction stability. As a more complex machine-learning model, ANN introduces "feed-forward" networks that increase flexibility and capture intricate interactions among predictors. We consider neural networks with one to four hidden layers linking the predicting and dependent variables (ANN1, ANN2, ANN3, ANN4). Thus, we consider at total of six nonlinear machine-learning models.

2.3 Out-of-sample evaluation of composite predictors

We evaluate the out-of-sample performance of the linear and nonlinear composite predictors using a rolling-window approach. Following Feng et al. (2020) and Gu et al. (2020), we first normalize the 16 predicting variables described in Section 2.1 (the quarterly trades and lagged quarterly holdings) by applying a transformation so that they are uniformly distributed between minus one and one.[7] Then, for the first estimation window spanning January 2008 to December 2012, we train each linear and nonlinear prediction model using stock-month structured panel data to predict next month's stock excess return, using the normalized variables as predictors. We then feed the normalized predicting variables for December 2012 into each of the trained models to forecast the excess return of each stock in January 2013. We then roll the estimation window one month forward and repeat this process.

At the end of this procedure, we have stock return forecasts for the 12 models for each month in our out-of-sample period from January 2013 to December 2020. To construct the linear composite return predictor (LCP) for each stock and out-of-sample month, we compute the average out-of-sample predictor across the six linear models: OLS, PCR, PLS, ALasso, Ridge, and ENet. Similarly, the nonlinear composite return predictor (NLCP) is the average across the six nonlinear model predictors: GBRT, RF, ANN1, ANN2, ANN3, ANN4. A detailed description of the method we use to fine-tune the hyperparameters of the machine-learning models is provided in Appendix A.3.

2.4 Descriptive statistics

Table 1 provides summary statistics (mean, median, standard deviation, and 10th and 90th percentiles) estimated at the stock-month panel-data level for the holdings and trades of the nine types of market participants, and for the linear and nonlinear composite return predictors.

[Insert Table 1 here]

[7] We replace missing values of the normalized predicting variables with their cross-sectional mean (zero), provided that there is data for at least one predicting variable. If there is no data for any predicting variable, then we drop the observation from the panel.

Panel A of Table 1 shows that mutual funds and other institutions (non-categorized 13F institutions) together hold around 40% of the shares outstanding, consistent with McLean et al. (2022). In contrast, the holdings from insurance companies and wealth management firms are much smaller, around 2–3% of shares outstanding each. The mean short seller holdings (short interest) is substantial at -15.46% of shares outstanding. The 10th and 90th percentiles show that there is wide variation in holdings across our panel data. For instance, mutual-fund holdings range from close to zero to just below 40%. Panel B of Table 1 shows that there is also variation across our panel data in the trades of the different types of investors. In particular, we observe that the 10th percentile of the trading variables is negative and the 90th percentile is positive for every type of investor. Panel C of Table 1 shows that the average linear composite return predictor (LCP) is 0.63%, while the average nonlinear composite return predictor (NLCP) is 1.22%. The NLCP shows a greater variation compared to the LCP, with a standard deviation of 0.83%.

3 Out-of-sample performance of return predictors

In this section, we evaluate the out-of-sample performance of the portfolios of stocks sorted by the return predictions obtained from the trades and holdings of the nine types of market participants. As a benchmark, Section 3.1 reports the performance of the univariate portfolios formed by sorting stocks based on the trades (or holdings) of a single type of market participants. Section 3.2 reports the performance of the portfolios based on the linear and nonlinear composite predictors obtained from the combined trades and holdings of all market participants. Section 3.3 uses Fama and MacBeth (1973) regressions to evaluate the performance of the composite predictors after controlling for common firm characteristics, and Section 3.4 to examine the significance of trades and holdings for the performance of the composite predictors. Finally, Section 3.5 studies the importance of the 16 predicting variables and their interactions for the predictions of the nonlinear machine-learning models.

3.1 Univariate portfolios

Although our work focuses on the information in the *combined* trades of multiple market participants, as a benchmark we also evaluate the performance of the univariate portfolios obtained by sorting stocks based on the trades (or holdings) of a single type of market participant. Panels A and B of Table 2 report the performance of the univariate portfolios constructed using trades and lagged holdings, respectively. For each panel, the first column reports the name of the sorting variable, the second to seventh columns report the alpha of the low, second, third, eight, ninth, and high decile portfolios, respectively, and the eighth column reports the alpha for the long-short portfolio, which goes long stocks in the high decile and short stocks in the low decile. At the end of each month, we rank all sample stocks based on either the trades or lagged holdings of each type of market participant and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile portfolio, as well as the long-short portfolio, and report their alphas with respect to the five Fama and French (2015) and momentum factors. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively.[8] To facilitate the comparison, we evaluate performance in the period from 2013 to 2020, which coincides with the out-of-sample period for the evaluation of the composite return predictors.

[Insert Table 2 here]

Panel A of Table 2 shows that the univariate long-short portfolios obtained from the trades of several types of investors achieve significant, although not always positive, alphas. For instance, the alphas of the long-short portfolios based on trades are significant at the 1% level for banks and other 13F institutions, at the 5% level for hedge funds, mutual funds, and retail investors, and at the 10% level for insurance companies and wealth management firms. However, the sign of the alphas demonstrates that only the trades of hedge funds, other 13F institutions, and retail investors (those from off-exchange markets) predict returns on the

[8] We use the R-package "NeweyWest" to select the bandwidth using the automatic procedure of Newey and West (1994).

right side. This is consistent with the existing literature that highlights the predictive power of hedge fund trades (Kosowski et al., 2007; Aggarwal and Jorion, 2010; Cao et al., 2018) and that of retail trades that goes beyond mere liquidity provision (Kaniel et al., 2012; Kelley and Tetlock, 2013; Boehmer et al., 2021).[9] Although the trades of other (uncategorized) 13F institutions have not received much attention in the existing literature, McLean et al. (2022) suggest that some of these trades may involve proprietary trading, which could explain their ability to predict returns on the right side. On the other hand, the monthly alpha of the long-short portfolio obtained from mutual fund trades is -0.39%, negative and significant at the 5% level, suggesting that mutual fund trades perform poorly. This is consistent with evidence in the existing literature that actively managed mutual funds (on average) underperform the market (Berk and Green, 2004; Fama and French, 2010). Finally, Panel A shows that the trades of insurance companies and wealth management firms also negatively predict returns significantly at the 10% level.[10]

Panel B of Table 2 reports the alphas of univariate portfolios of stocks sorted by lagged holdings. The only univariate long-short portfolio based on holdings that achieves a significant alpha is that based on short seller holdings, which has a substantial monthly alpha of 1.51%. The alphas for the decile portfolios based on the holdings of the rest of market participants do not exhibit a clear monotonic pattern from the low to the high deciles. Across all top deciles, only the high decile of stocks sorted by short seller holdings shows strong return predictability, with monthly return as high as 1.04% and significant at the 1% level. As explained in Section 2.1, we use short interest as a proxy for short seller holdings and we change its sign so that a higher value corresponds to less shorting. The low decile of short seller holdings earns a significantly negative alpha of -0.47%. These findings align with the existing

[9] In contrast, earlier work showed that retail investors as a group can be uninformed and irrational (Barber and Odean, 2000; Barber et al., 2009)

[10] The results in Panel A of Table 2 are consistent with some of those in table 8 of McLean et al. (2022). For instance, both tables show that bank trades negatively predict returns and retail trades identified using the Boehmer et al. (2021) or Barber et al., 2024 algorithms positively predict returns. However, there are also some differences. For example, while McLean et al. (2022) find that short seller trades and firm trades positively predict returns, we find that the trades of hedge funds and other institutions positively predict returns. Also, while McLean et al. (2022) find that institutional trades (other than those of banks) generally do not predict returns individually, we find that the trades of insurance companies, mutual funds, and wealth management firms negatively predict returns. The differences are explained by two main factors. First, while the sample data of McLean et al. (2022) spans 2006 to 2017, ours spans from 2013 to 2020. Second, while McLean et al. (2022) aggregate trades annually, we aggregte them quarterly.

literature, which demonstrates that low levels of short interest signal positive information about future stock returns, while high levels indicate negative information (Desai et al., 2002; Asquith et al., 2005; Diether et al., 2009; Karpoff and Lou, 2010; Boehmer et al., 2010).[11]

3.2 Composite return predictors

In this section, we evaluate the out-of-sample performance of the portfolios of stocks sorted by the linear (LCP) and nonlinear (NLCP) composite predictors and study the impact of transaction costs on their performance. We also examine the persistence over time of the performance of the NLCP-based portfolios.

Table 3 reports the alpha of the portfolios of stocks sorted by the LCP and NLCP. The first column reports the label for each decile portfolio and the long-short portfolio, the second and third columns report the alpha of each portfolio based on the LCP with respect to the five Fama and French (2015) and momentum factors (FF5+MOM) and the five Hou et al. (2021) and momentum factors (q5+MOM), the fourth and fifth columns for the portfolios based on the NLCP, and the sixth and seventh columns for the difference between the returns of the portfolios based on NLCP and LCP (NLCP minus LCP). At the end of each month, we rank all sample stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile portfolio, as well as on the long-short portfolio, and report their alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

[Insert Table 3 here]

The portfolios based on the linear composite predictor (LCP) achieve good out-of-sample performance. For instance, the second and third columns of Table 3 show that the alphas of the LCP decile portfolios increase, although not always monotonically, from the low (L) to the high (H) decile. Moreover, the LCP long-short portfolio (H-L) generates a significant

[11] The performance of the univariate portfolios in terms of alpha with respect to the five Hou et al. (2021) and momentum factors is reported in Table B.1 of Appendix B and leads to similar conclusions.

monthly FF5+MOM alpha of 1.78% (t-stat = 10.03) and q5+MOM alpha of 1.68% (t-stat = 6.01). The alphas of the LCP long-short portfolio are also significantly higher than those of the univariate long-short portfolios, with the exception of the portfolio based on short seller holdings, for which although the alpha of the LCP long-short portfolio is more than 10% higher, the difference is not significant. Overall, we find that there are benefits from linearly combining the information in the trades and holdings of multiple market participants.

The portfolios based on the nonlinear composite predictor (NLCP) perform even better than those based on the LCP. For instance, the fourth and fifth columns of Table 3 show that the NLCP low and high decile portfolios achieve significant monthly FF5+MOM alphas of -1.49% (t-stat = -4.11) and 1.25% (t-stat = 4.87), which are more than 50% higher in absolute value than those of the LCP low and high decile portfolios. Also, the NCLP long-short portfolio generates significant monthly FF5+MOM alpha of 2.74% (t-stat = 9.80) and q5+MOM alpha of 2.60% (t-stat = 7.60), which are also more than 50% higher than those of the LCP long-short portfolio, with the difference being significant at the 1% confidence level as shown in the sixth and seventh columns of Table 3. Moreover, we find that the alphas of the NLCP long-short portfolio are also significantly higher than those of the univariate long-short portfolios, including that based on short seller holdings. These results highlight the benefits from exploiting nonlinearities and interactions in the relation between the trades and holdings and future stock returns, consistent with the recent literature that emphasizes the importance of nonlinearities and interactions in the prediction of asset returns (Kelly et al., 2019; Gu et al., 2020; Bianchi et al., 2021; Bryzgalova et al., 2021; Binsbergen et al., 2022).[12]

Like Gu et al. (2020), our statistical objective functions minimize equally weighted forecast errors, and thus, we focus our discussion primarily on the results for equal-weighted portfolios. However, in Section 4.1, where we examine the return predictability of our composite predictors under different information environments, we also evaluate the performance of the LCP and NLCP portfolios across sub-samples of stocks with different firm sizes. We find that the LCP and NLCP long-short portfolio alphas remain generally significant across small, medium, and large stocks, for both equal- and value-weighted portfolio returns. How-

[12]Table B.2 in Appendix B reports the performance of the long-short portfolios obtained based on each of the twelve predictive models individually. The alphas for all methods are statistically significant at the 1% level.

ever, there are benefits from exploiting nonlinearities and interactions (compared to using a linear approach) only for small and medium stocks.

The favorable out-of-sample performance of the LCP and NLCP long-short portfolios is also robust to considering proportional transaction costs of 60 basis points. Table 4 reports the alpha of the LCP and NLCP long-short portfolios, as well as the alpha for the difference between the returns of the NLCP and LCP long-short portfolios in the presence of proportional transaction costs of 30 and 60 basis points. The first column reports the level of transaction costs, the second and third columns report the alpha of the LCP long-short portfolio with respect to the five Fama and French (2015) and momentum factors (FF5+MOM) and the five Hou et al. (2021) and momentum factors (q5+MOM), the fourth and fifth columns for the NLCP long-short portfolio, and the sixth and seventh columns for the difference between the returns of the NLCP and LCP long-short portfolios (NLCP minus LCP). Although the alphas of the LCP and NLCP long-short portfolios decrease with transaction costs, they remain statistically significant at the 1% level even in the presence of transaction costs of 60 basis points. Moreover, the table shows that the monthly alpha of the NLCP long-short portfolio is around 60 basis points higher than that of the LCP long-short portfolio in the presence of transaction costs of 60 basis points, with the difference being significant at the 5% level for the FF5+MOM model and at the 10% level for the q5+MOM model.[13]

[Insert Table 4 here]

We now examine the persistence of the performance of the NLCP-based portfolios. Table 5 reports the monthly alpha of the long-short portfolios of stocks sorted by LCP and NLCP, for specific months after portfolio formation, ranging from the first month to the 24th month after portfolio formation. The first column reports the number of the month following portfolio formation. The second and third columns report the FF5+MOM and q5+MOM alphas of the LCP long-short portfolio, the fourth and fifth columns for the NLCP long-short portfolio, and the sixth and seventh columns for the difference between the returns of the NLCP and LCP long-short portfolios (NLCP minus LCP). At the end of each month, we rank all sample

[13]We find that the monthly turnover of the LCP and NLCP long-short portfolios is 42.14% and 70.19%.

stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted excess returns on the long-short portfolio, for up to 24 months after portfolio formation, and report the alphas for each month separately.

[Insert Table 5 here]

Table 5 shows that the LCP long-short portfolio continues generating monthly alphas above 1% for up to nine months after portfolio formation, which are significant at the 1% level with respect to the FF5+MOM model and at the 5% level with respect to the q5+MOM model. The monthly alphas of the NLCP long-short portfolio are even more persistent, remaining above 1% for up to 15 months after portfolio formation and significant at the 1% level with respect to the FF5+MOM model and at the 5% level with respect to the q5+MOM model. The monthly alpha of the NLCP long-short portfolio is higher than that of the LCP long-short portfolio for all 24 months after portfolio formation, with the difference remaining statistically significant for the first two months. Moreover, the difference is statistically significant at the 10% level for 10 out of 24 months after portfolio formation for the FF5+MOM model and 14 out of 24 months for the q5+MOM model. Overall, we find that the out-of-sample performance of the NLCP long-short portfolios is robust to evaluating its alpha for up to 15 months after portfolio formation.

3.3 Controlling for firm characteristics

Although the LCP and NLCP portfolios generate significant alpha with respect to the FF5+MOM and q5+MOM factor models, their predictive power may still be subsumed by common firm characteristics not included in these models. To address this, we use Fama-MacBeth regressions to control for firm characteristics known to predict stock returns. Because Table 3 indicates that the composite predictors predict returns most significantly for the high and low deciles, we create indicator variables for these predictors. Each month, we sort sample stocks into decile portfolios based on their LCP or NLCP values. The indicator variables, I_LCP and I_NLCP, are set to one if the corresponding LCP or NLCP falls within the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of stock

returns on these indicator variables controlling for the following firm characteristics: firm size (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), asset growth (AG), gross profitability (GP), turnover (TO), and idiosyncratic volatility (IVOL).[14] We winsorize characteristics at the 1st and 99th percentiles and standardize them to have zero mean and unit standard deviation.

[Insert Table 6 here]

The second and third columns of Table 6 report the results for the Fama-MacBeth regressions that include the indicator variables individually. We observe that the spread in expected monthly return between stocks in the high and low deciles of LCP is 0.65%, while the spread for NLCP is more than double, at 1.54%. Note that this spread is double the slope coefficient of the indicator variables, as these variables range from minus one to one. The fourth column reports the regression results when we include both indicator variables. The slope coefficient for the NLCP indicator variable remains largely unchanged, but the coefficient for the LCP indicator variable is close to zero and no longer significant.

The results in Tables 2– 6 overall highlight the importance of aggregating the trades and holdings from multiple market participants using machine learning. The NLCP, which contains information extracted from nonlinear interactions among predictors, is a particularly strong return predictor.

3.4 Trading-based and holdings-based composite predictors

Both the linear and nonlinear composite predictors rely on the trades and lagged holdings of market participants. As discussed in the introduction, both trades and lagged holdings of investors may predict stock returns. Trades may reflect more recent or short-term information. Lagged holdings could indicate investors' persistent demand for the stock and hence reflect

[14] In detail, firm size (SIZE) is natural logarithm of market capitalization. Book-to-market ratio (BM) is most recent fiscal year-end book value divided by market capitalization. Momentum (MOM) is cumulative return over the last 12 months excluding last month. Short-term reversal (STR) is previous month's return. Asset growth (AG) is annual asset growth from previous fiscal year. Gross profitability (GP) is gross profit divided by total assets from last fiscal year. Turnover (TO) is trading volume divided by number of shares outstanding in previous month. Idiosyncratic volatility (IVOL) is standard deviation of the residuals from the three-factor Fama and French (1992) model of daily stock excess returns over the past six months.

price pressure (Gompers and Metrick, 2001). They may also embed long-term information about the firm that affects future returns. In this section, we assess the relative significance of trades and lagged holdings for the composite return predictors. To do this, we generate linear and nonlinear composite predictors based on either only the combined trades or only the combined holdings of all market participants.

Table 8 reports the results for the Fama and MacBeth (1973) regressions of monthly stock returns on indicator variables obtained using the composite predictors based on only the trades (LCP_Trading and NLCP_Trading) or only the lagged holdings (LCP_Holding and NLCP_Holding) of all market participants. The indicator variables are equal to one if the corresponding composite predictor is within the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of stock returns on the indicator variables and the firm characteristics defined in Section 2.4. The first column reports the symbol of each explanatory variable, the second, third, fourth, and fifth columns report the results for the regressions that include individually the LCP_Trading, LCP_Holding, NLCP_Trading, or NLCP_Holding indicator variables, respectively, and the sixth column for the regression that includes all four indicator variables.

[Insert Table 8 here]

The second to fifth columns of Table 8 show that (individually) both the trading- and holdings-based predictors, linear or nonlinear, significantly predict monthly stock returns. The coefficient on the NLCP_Holdings indicator variable is the largest, followed by those of the NLCP_Trading, LCP_Holdings, and LCP_Trading indicator variables, in this order. The coefficients are also economically significant: the spread in expected monthly return between a stock in the high and low deciles is 1.16% for NLCP_Holdings, 0.85% for NLCP_Trading, 0.65% for LCP_Holdings, and 0.43% for LCP_Trading. The sixth column shows that, when we include all four indicator variables in Fama-MacBeth regressions, only the trading- and holdings-based NLCP exhibit significant predictability. The coefficients of the linear predictors are no longer statistically significant. The holdings component contributes about 59.2% to the NLCP predictability, while the trading component contributes 40.8%. These results confirm

that when put together, NLCP dominates LCP, highlighting the importance of capturing the nonlinear interactions among the trades and holdings of various market participants.

3.5 Variable and interaction importance

In this section, we investigate the relative importance of the 16 predicting variables and their interactions for the predictions of the nonlinear machine-learning models. To do this, we estimate the SHAP values of Lundberg and Lee (2017), which have been used in finance by Bali et al. (2023) and DeMiguel et al. (2023). SHapley Additive exPlanations (SHAP) is a method based on cooperative game theory and used to estimate the contribution of each variable to the prediction for each observation. SHAP is an additive method because aggregating SHAP values across variables, one recovers the difference between the prediction for an individual observation and the average prediction across all observations.[15] To reduce the heavy computational workload associated with computing SHAP values, we focus our analysis on the random-forest model.

[Insert Figure 2 here]

Figure 2 illustrates the importance of each of the 16 predicting variables for random forest. We estimate variable importance by averaging the absolute SHAP values of each variable across all observations within the last estimation window, which spans December 2015 to November 2020. Figure 2 demonstrates that there is no single variable that is driving the predictions of random forest. To see this, note that all top five variables have relatively large average absolute SHAP values above 0.00075. In contrast with the finding that the univariate portfolio based on short seller holdings generates a large and significant alpha, short seller holdings is not among the top ten most important variables for random forest. This suggests that, when we consider (jointly) the trades and holdings of multiple market participants, the

[15]The SHAP method is model-agnostic, applicable to any type of data, and provides additive interpretation (contribution of each characteristic to the prediction) of machine-learning models, including feature importance, feature dependence, interactions, clustering and summary plots. Moreover, the tree-based versions take into account the dependencies between variables (Lundberg et al., 2020). For these reasons, SHAP has recently become the method of choice to visualize variable and interaction importance. For a general discussion see Molnar (2019) and for applications in finance see Pedersen (2022).

informational content of short seller holdings is subsumed by other predicting variables.

[Insert Figure 3 here]

Panel A of Figure 3 graphs the importance of each of the nine investor types estimated as the average absolute value of the sum of the SHAP values for the trading and holding variables corresponding to each investor. Panel A shows that the top three most important types of investors for the prediction of random forest are mutual funds, insurance companies, and wealth management firms. Panel B of Figure 3 graphs the importance of trading versus lagged holding variables measured as the average across all observations of the absolute value of the sum of the SHAP values for all trading or lagged holding variables. The graph shows that lagged holdings are important for the predictions of random forests, with an average absolute SHAP value around 0.0034. However, consistent with the results in Section 3.4, Panel B of Figure 3 shows that the trading variables contain information (beyond that contained in lagged holding variables) that is valuable for the predictions of random forest. Specifically, the graph shows that the average absolute SHAP value of trading variables is close to 0.0025.

[Insert Figure 4 here]

Note that we measure variable importance using the average *absolute* SHAP value, and thus, the bar charts in Figure 2 do not allow one to determine whether the relation between a variable and future returns is positive or negative. This information can be observed from the beeswarm plot in Figure 4, which summarizes the impact of each variable on the random forest predictions. Each variable is represented by a row in the beeswarm plot, and the sixteen variables are ordered by their importance (average absolute SHAP value). Each observation is represented by a single dot in each variable row, with its position on the horizontal axis given by the SHAP value of the variable for that observation. Dots "pile up" along each feature row to show density. Color is used to display the original value of a variable (feature value). Figure 4 shows that several of the most important variables are negatively related to future returns. For instance, the beeswarm dots in the row for mutual fund trades are colored in red for negative SHAP values and in blue for positive SHAP values. That is, consistent with the

results for the univariate portfolios, high (low) values of mutual fund trades predict negative (positive) future returns. A similar pattern can be observed for lagged mutual fund holdings and lagged insurance company holdings. For other variables the beeswarm plots suggest that there may be a nonmonotonic relation between the variable and future returns. For instance, the beeswarm for insurance company trades contains red and purple dots both for positive and negative SHAP values. This suggests there may be an interaction between insurance company trades and other predicting variables.

[Insert Figure 5 here]

Figure 5 illustrates the importance of the top 20 interactions among pairs of variables. We estimate interaction importance by averaging the absolute SHAP *interaction* value across all observations within the last estimation window. The top four interactions correspond to pairs of lagged institutional holdings (bank holdings and other 13F holdings, hedge fund holdings and other 13F holdings, mutual fund holdings and insurance firm holdings, and mutual fund holdings and wealth management holdings). To understand the nature of these interactions, the four panels of Figure 6 give a SHAP plot for each of these interactions. For each panel, the horizontal axis depicts the (standardized) first variable in the interaction and the vertical axis its SHAP value for each observation (black dots). To visualize the interaction, we split all observations into quintiles of the second variable and depict, for each quintile, the conditional mean SHAP value of the first variable (lines).

[Insert Figure 6 here]

The pattern in the four SHAP plots in Figure 6 is quite similar. For instance, Panel C depicts the interaction between lagged mutual fund holdings and lagged insurance company holdings. To simplify the exposition, in the remainder of this section we drop the term "lagged" from the name of holding variables. Our first observation is that there is a strong interaction between mutual fund holdings and insurance company holdings. To see this, note that the lines depicting the conditional SHAP value of mutual fund holdings for each quintile of insurance company holdings differ substantially across quintiles, particularly for negative

values of mutual fund holdings. For quintiles 3, 4, and 5 (high insurance company holdings), the lines indicate a positive and monotonic relation between mutual fund holdings and future returns for negative values of standardized mutual fund holdings, and a mostly flat relation for positive values of standardized mutual fund holdings. In contrast, the lines for quintiles 1 and 2 (low insurance company holdings) have an inverted-U shape. For instance, the line for the first quintile is steeply increasing in mutual fund holdings in the range from -1.0 to around -0.85, decreasing from -0.85 to 0.0, and mildly increasing for positive values of mutual-fund holdings. That is, while there is a positive monotonic relation between mutual fund holdings and SHAP values for stocks with high insurance company holdings, there is a nonmonotonic, inverted-U shape for stocks with low insurance company holdings.

[Insert Figure 7 here]

Figure 5 shows that there are also important interactions between trading variables and holding variables. For instance, among the top 20 interactions, there are several interactions between the trades of several institutional investors and the holdings of other 13F institutions, defined as institutions that we cannot classify as either mutual funds, hedge funds, banks, insurance companies, or wealth management firms. To investigate the nature of these interactions, the three panels in Figure 7 illustrate the interactions between the trades of three types of institutions and the holdings of other 13F institutions. For instance, Panel A depicts the interaction between mutual fund trades and lagged holdings of other 13F institutions. The horizontal axis depicts the (standardized) mutual fund trades and the vertical axis their SHAP value for each observation (dots). To visualize the interaction, we use color to display the original value of the lagged holdings of other 13F institutions (red for high value and blue for low value).

Panel A of Figure 7 shows that, consistent with our findings from the beeswarm plot in Figure 4, there is a negative relation between mutual fund trades and future returns, that is, the aggregate quarterly trades of mutual funds negatively predict next month stock returns. However, the dot coloring pattern demonstrates that this negative relation is particularly pronounced for stocks that were being held by other 13F institutions in the previous quarter (red

dots). To see this, note that the red dots tend to have the highest SHAP values for negative values of standardized mutual fund trades, but the lowest for positive values of standardized mutual fund trades. Panel B illustrates the interaction between insurance company trades and holdings of other 13F institutions, showing that there is (on average) a positive relation between the trades of insurance companies and future returns. However, the relation is almost flat for stocks that were being held by other 13F institutions in the previous quarter (red dots). Panel C illustrates the interaction between wealth management firm trades and lagged holdings of other 13F institutions and it shows a very similar pattern to that in Panel B.[16]

The results in this section show that, while some investors (for instance, mutual funds, insurance companies, and wealth management firms) appear more important, there is no single type of investors that drives the predictions of random forest. Consistent with our findings from the Fama-MacBeth regressions, we find that both trades and lagged holdings are important for random forest. However, in contrast with the finding that the univariate portfolio based on short seller holdings generates a highly significant alpha, short seller holdings is not among the most important variables for random forest. This suggests that, when we consider (jointly) the trades and holdings of multiple market participants, the informational content of short seller holdings is subsumed by other predicting variables. Finally, we find that random forest exploits the interactions between the lagged holdings of different types of investors as well as between the trades of some investors and the lagged holdings of other investors.

4 Information environment and firm fundamentals

Prior studies show that expected stock returns are positively related to ex-ante information asymmetry (Diamond and Verrecchia, 1991; Verrecchia, 2001; O'Hara, 2003; Easley and

[16] Figure 7 shows that the holdings of other 13F institutions play an important role in many of the interactions that are exploited by random forest. As mentioned above, we classify as "other" those institutions that we are not able to classify as either mutual funds, hedge funds, banks, insurance companies, or wealth management firms. Thus, other institutions in our dataset are likely to consist of a mixed of different types of institutional investors, and thus, other holdings may represent a proxy for general institutional holdings. Figure B.1 in Appendix B provides evidence for this hypothesis by depicting the interactions between the trades of mutual funds, insurance companies, and wealth management firms and the lagged holdings of the *remaining institutions*. For instance, Panel A depicts the interaction between mutual fund trading and the aggregate lagged holdings of institutional investors other than mutual funds. The three panels in Figure B.1 confirm that the insights from Figure 2 are robust to coloring the dots using the lagged holdings of all remaining institutions instead of the holdings of other institutions.

O'Hara, 2004). If the composite return predictors reflect valuable information that is not yet absorbed by the market, their ability to predict returns should be stronger for stocks with greater information uncertainty. In addition, they may predict future firm fundamentals and earnings announcement returns. In this section, we test these hypotheses.

4.1 Portfolio performance and firm size

We first study how the LCP and NLCP portfolio returns vary across subsamples of stocks with different market capitalization. Given the evidence in the literature that there is greater information uncertainty about smaller firms (e.g., Atiase, 1985; Bamber, 1987; Llorente et al., 2002), we would expect that the predictive power of the composite predictors should be stronger for smaller firms. To test this hypothesis, we first sort all sample stocks into terciles by firm size at the end of each month. Then, within each tercile, we further sort stocks into decile portfolios based on the LCP or NLCP. We hold the stocks for one month. Table 9 reports the FF5+MOM alphas of the LCP and NLCP portfolios across terciles of stocks with different firm sizes.

[Insert Table 9 here]

Overall, both the LCP and NLCP show significant return predictability across different firm sizes. Consistent with the evidence that information asymmetry is greater for smaller firms, the long-short portfolio alphas are highest for small stocks, at 3.27% for the LCP and 3.68% for the NLCP, both significant at the 1% level. Alphas decrease substantially with firm size. For medium stocks, the long-short portfolio alphas for the LCP and NLCP are smaller at 1.03% and 1.29%, but they remain significant at the 1% level. For large stocks, the long-short portfolio alphas further decrease to 0.65% for LCP and 0.26% for NLCP, and while the LCP alpha remains significant at the 1% level, the NLCP alpha is significant only at the 10% level. Comparing the LCP and NLCP alphas across the terciles of stocks sorted by size, we find that the benefits of exploiting nonlinearities and interactions, as opposed to using a linear model, are present only for small and medium stocks.[17]

[17] Table B.4 in Appendix B reports the alphas for the value-weighted portfolios. Consistent with the findings

To disentangle the effect of size on the performance of the LCP and NLCP, Table 7 reports the results from estimating Fama-MacBeth regressions with the same explanatory and dependent variables as in Table 6, but including interactions between firm size and the LCP and NLCP indicator variables. We find that while the interaction between size and the LCP indicator variable is not significant, that between size and the NLCP is significantly negative. This shows that the spread in expected returns between the top and bottom deciles generated by the NLCP is significantly larger for smaller stocks. Importantly, the results in the fourth column of Table 7 show that, when we include the LCP and NLCP indicator variables and their interactions with size simultaneously in Fama-MacBeth regressions, only the NLCP indicator variable and its interaction with size remain significant. Thus, the predictability of the NLCP dominates that of the LCP in Fama-MacBeth regressions even when we control for the interaction terms of NLCP and firm size.

[Insert Table 7 here]

4.2 Effect of information environment

We next examine how the predictive power of the composite return predictors varies across sub-samples of stocks categorized by other commonly-used proxies for uncertainty and information asymmetry such as firm age, idiosyncratic volatility, illiquidity, and analyst coverage and disagreement (Llorente et al., 2002; Amihud, 2002; Yu, 2008; Diether et al., 2002). We measure firm age as the number of years since the firm was first covered by CRSP, idiosyncratic volatility as the standard deviation of the residuals from regressing daily excess stock returns on the three-factor Fama and French (1992) model over the previous six months, illiquidity following Amihud (2002), analyst coverage as the number of analysts with valid earnings per share forecast as of prior month-end, and analyst disagreement as analyst forecast dispersion (standard deviation of analyst forecasts divided by absolute value of average analyst forecast in the prior month). At the end of each month, we sort all sample stocks into halves based

in Table 9, both the LCP and NLCP value-weighted long-short portfolios earn significant alphas for medium and small stocks, although with smaller magnitudes. For large stocks, the alpha for LCP remains comparable in magnitude to the equal-weighted results and is significant at the 1% level, while the alpha for NLCP is no longer statistically significant.

on an information-asymmetry proxy. We then run Fama and MacBeth (1973) regressions of stock returns on the I_LCP and I_NLCP indicator variables, and the firm characteristics defined in Section 3.3 for each sub-sample, and report the results in Table 10.

[Insert Table 10 here]

We find that the spread in the expected returns of firms with high versus low NLCP is higher for firms with higher idiosyncratic volatility, higher illiquidity, lower analyst coverage, and higher analyst disagreement, although it is similar for young versus old firms. This is generally consistent with our conjecture that the NLCP predictability should be stronger for stocks with more uncertain information environment. We also find that the coefficient on the LCP indicator variable is not significant when we control for the NLCP indicator variable in the regressions, consistent with the findings from Table 6.

4.3 Predicting fundamentals and earnings announcement returns

We now test whether the LCP and NLCP contain information about future firm fundamentals related to operating performance and earning announcement returns. We consider four measures of operating performance: cash flows (CF), which is the difference between income before extraordinary items and total accruals, divided by total assets, gross margin (GM), which is is sales minus cost of goods sold scaled by current sales, return-on-equity (ROE), which is the sum of income before extraordinary items and interest expenses, divided by the lagged total equity, and return-on-asset (ROA), which is the sum of income before extraordinary items and interest expenses, divided by the lagged total assets. Earnings announcement returns (CAR) are cumulative abnormal returns in the $[-1, 1]$ three-day window around the earnings announcement day, where abnormal returns are the difference between the daily stock return and that of the corresponding portfolio among the six size and book-to-market Fama-French portfolios.

Table 11 reports the results for the Fama and MacBeth (1973) regressions of future operating performance and earning announcement returns on the indicator variables I_LCP and I_NLCP, controlling for the firm characteristics defined in Section 3.3. In addition, to

account for auto-correlation in operating performance, we include the lagged values of the dependent variables as controls in the regressions.

[Insert Table 11 here]

Table 11 shows that the NLCP indicator variable significantly predicts future CF, GM, ROE, and ROA. Compared to a stock in the low NLCP decile, a stock in the high NLCP decile has an expected next-quarter CF ratio 0.914% higher, GM ratio 0.506% higher, ROE ratio 1.554% higher, and ROA ratio 1.252% higher, with all these differences being statistically significant at the 5% confidence level.[18] The results are qualitatively similar for the LCP indicator variable, except that the spread between the expected next-quarter ROE of stocks in the high and low LCP deciles is not statistically significant. Specifically, compared to a stock in the low LCP decile, a stock in the high LCP decile has an expected next-quarter CF ratio 0.95% higher, GM ratio 0.52% higher, and ROA ratio 0.98% higher.

Given that the NLCP can predict future firm fundamentals, it should also predict future earnings announcement returns, which capture the combined effect of reported fundamentals on stock returns. Indeed, Table 11 shows that the NLCP indicator variable significantly predicts future earnings announcement returns after controlling for firm characteristics. The spread between the expected earnings announcement return of stocks in the high and low NLCP deciles is 0.56%, significant at the 1% level. The LCP indicator variable, on the other hand, does not significantly predict earnings announcement returns.

Overall, these results suggest that the return predictability of the composite predictors originates at least partially from their ability to predict future firm fundamentals and earnings announcement returns.

5 Asset-pricing implications

In this section, we examine the asset-pricing implications of the composite return predictors. In particular, we study whether the composite return predictors assign stocks on the

[18] As mentioned before, the spread in expected operating performance between the high and low deciles is double the slope coefficient of the indicator variables, as these variables range between minus one and one.

right side of anomalies, and whether a factor model constructed using the composite predictors spans the investment opportunity set.

5.1 Stock anomalies and composite predictors

The literature has studied whether the trades of different market participants are consistent with the predictability of well-known stock anomalies. For example, Edelen et al. (2016) show that institutional investors tend to trade on the wrong side of anomalies. McLean et al. (2022) conduct a more systematic analysis of the trades of nine types of market participants, and find that while retail investors tend to trade on the wrong side of anomalies, firms and short sellers trade (on average) on the right side of anomalies. To gauge the information about anomalies contained in the composite return predictors, we compute the value of various anomalies for each decile portfolio of stocks sorted by LCP and NLCP.

We follow Green et al. (2017) to construct 102 anomalies based on firm characteristics. We then select the 12 anomalies whose returns are significant (t-stat >1.66) for our sample period from 2008 to 2020. The 12 significant anomalies are market capitalization (Banz, 1981), book-to-market (Rosenberg et al., 1985), gross margin (Novy-Marx, 2013), illiquidity (Amihud, 2002), idiosyncratic volatility (Ali et al., 2003), momentum_12m (Jegadeesh, 1990), momentum_1m (Jegadeesh and Titman, 1993), asset growth (Cooper et al., 2008), dividend yield (Litzenberger and Ramaswamy, 1981), analyst coverage (Elgers et al., 2001), price delay (Hou and Moskowitz, 2005), and combined fundamental (Mohanram, 2005). Table 12 reports the time-series average of the cross-sectional means of firm characteristics corresponding to the 12 stock anomalies for portfolios sorted by either LCP or NLCP. For easier interpretation, we change the sign of the four anomalies whose return is negative (market capitalization, idiosyncratic volatility, momentum_1m, and asset growth), so that the mean anomaly values for the LCP and NLCP long-short portfolios should be positive if they select stocks on the right side of the anomalies.

[Insert Table 12 here]

Panel B of Table 12 shows that the characteristic spreads for the NLCP long-short port-

folio are significantly positive for 10 out of the 12 anomalies. Thus, the NLCP selects stocks on the right side of most anomalies. A notable exception is analyst coverage, for which the assignment of stocks based on the NLCP is significantly misaligned with the anomaly. The results for LCP in Panel A are very similar, except that the characteristic spreads are significantly positive for only eight characteristics. These findings indicate that, despite relying only on market participant trades and lagged holdings, the composite return predictors replicate some of the information available in well-known stock anomalies.

5.2 Factor models constructed from composite predictors

The results in the previous section show that both composite predictors are (on average) aligned with most anomalies. In this section, we further explore whether a factor model constructed using the LCP or NLCP can help to explain anomaly returns.

Table 13 reports the performance of several factor models in terms of their ability to explain anomaly returns and the Sharpe ratio generated by their factors. We consider four factor models: (i) the five Fama and French (2015) and momentum factors (FF5+MOM), (ii) the five Hou et al. (2021) and momentum factors (q5+MOM), (iii) a two-factor model including the market factor and the LCP factor defined as the return of the LCP equal-weighted long-short portfolio (LCP+MKT), and (iv) a two-factor model including the market factor and the NLCP factor defined as the return of the NLCP equal-weighted long-short portfolio (NLCP+MKT). We run time series regressions of the returns of the 12 significant anomalies on each of the four factor models. The first and second rows in the table report the average (across the 12 anomalies) of the absolute value of the alpha and alpha t-stat. The third row in the table reports the annualized Sharpe ratio of the mean-variance portfolio of the factors in each model, and the fourth and fifth rows report the p-value for the difference between the Sharpe ratio of each model and that of the FF5+MOM and q5+MOM models.

[Insert Table 13 here]

Table 13 shows that the average absolute value of the alpha of the 12 anomalies with respect to the LCP and NLCP factor models is 0.46 and 0.50, with average absolute t-statistics

of 1.19 and 1.16. For comparison, the average absolute alpha with respect to the FF5+MOM and q5+MOM models is 0.59 and 0.44, with average absolute t-statistics of 2.03 and 1.41. That is, the two-factor model with only the market and our LCP or NLCP factor performs similar to the prominent FF5+MOM and q5+MOM models in terms of its ability to explain anomaly returns. This is a notable result because the LCP and NLCP factors are constructed using only trades and holdings of market participants, ignoring any anomaly information.

Barillas and Shanken (2018) show that (under the assumption that a good factor model should span not only the test assets but also the factors in other models) test assets are irrelevant and it suffices to compare models in terms of the Sharpe ratio generated by their factors. We find that the NLCP factor model produces an annualized Sharpe ratio of 3.09, which is substantially higher than those generated by the FF5+MOM, q5+MOM, and LCP models (1.13, 1.71, and 2.32, respectively). Moreover, the difference between the Sharpe ratio of the NLCP model and those of the FF5+MOM and q5+MOM models is significant.

In summary, the Sharpe ratio results confirm that the nonlinear interaction effects exploited by the NLCP contain information that helps to span the overall investment opportunity set better than the LCP and existing factor models. In other words, the NLCP identifies information that while being important for asset pricing, is not captured by either existing factor models or the set of anomalies we consider.

6 Conclusion

We use machine learning to study whether trades and holdings of multiple market participants contain information about stocks. Our machine learning approach captures nonlinearities and interactions in the relation between trades and holdings and future stock returns. A long-short portfolio based on the nonlinear composite predictor (NLCP) yields monthly alphas with respect to prominent factor models exceeding 2.5%. The predictive power of the NLCP is not driven by just a few types of market participants, and both trades and holdings as well as their interactions are important to predict returns.

The predictability of the NLCP is stronger for smaller or illiquid stocks and stocks with lower analyst coverage or higher idiosyncratic volatility, suggesting that the information in

the NLCP is more useful for firms with higher information uncertainty. The NLCP contains information about firm fundamentals (predicting future cash flows, gross margin, and return on assets) and predicts also earnings announcement returns. Furthermore, the NLCP assigns stocks on the right side of most anomalies and a two-factor model with the market factor and an NLCP-based factor generates higher Sharpe ratio than prominent factor models. Overall, our findings suggest that combining the trades and holdings of multiple participants and accounting for nonlinearities and interactions provides valuable information for price discovery.

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Figure 1. Alpha of long-short portfolios based on univariate and composite predictors

This figure depicts the alpha of the long-short portfolios of stocks sorted by the trades or holdings of a single type of market participant, as well as the linear (LCP) and nonlinear (NLCP) composite predictors. Alphas are computed with respect to the Fama and French (2015) and momentum factors (FF5+MOM). At the end of each month, we rank all sample stocks based on the trades or holdings of a single type of market participant, LCP, or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted returns on the long-short portfolio that buys the high decile and shorts the low decile, and report their alphas. We compute Newey-West-adjusted t-statistics and report only the alphas that are significant at least at the 10% level. The out-of-sample period for the evaluation of the long-short portfolio returns spans from 2013 to 2020.

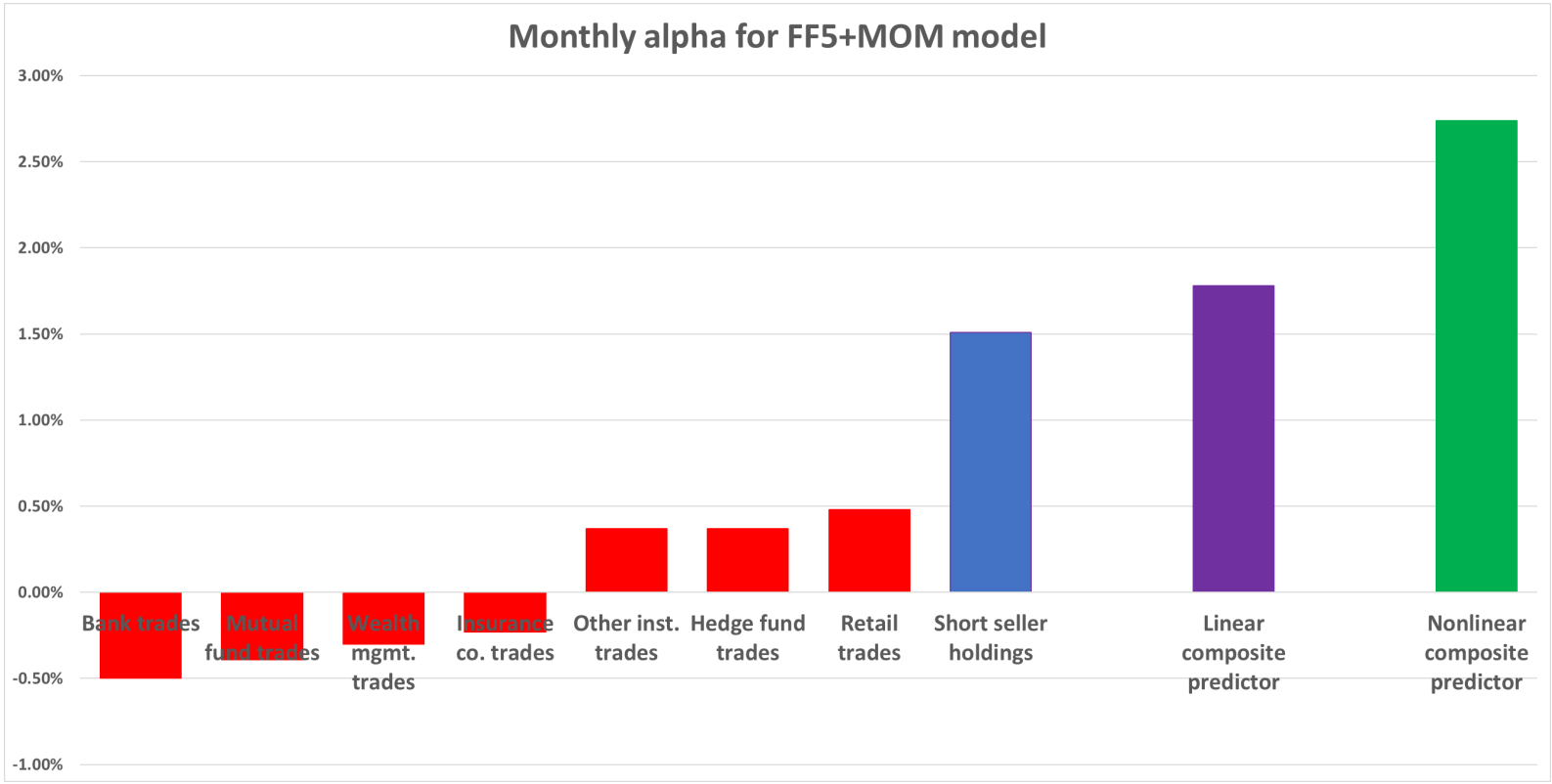


Figure 2. Variable importance

This figure illustrates the importance of each of the 16 predicting variables for random forest. We estimate variable importance by averaging the absolute SHAP values of each variable across all observations within the last estimation window, which spans December 2015 to November 2020.

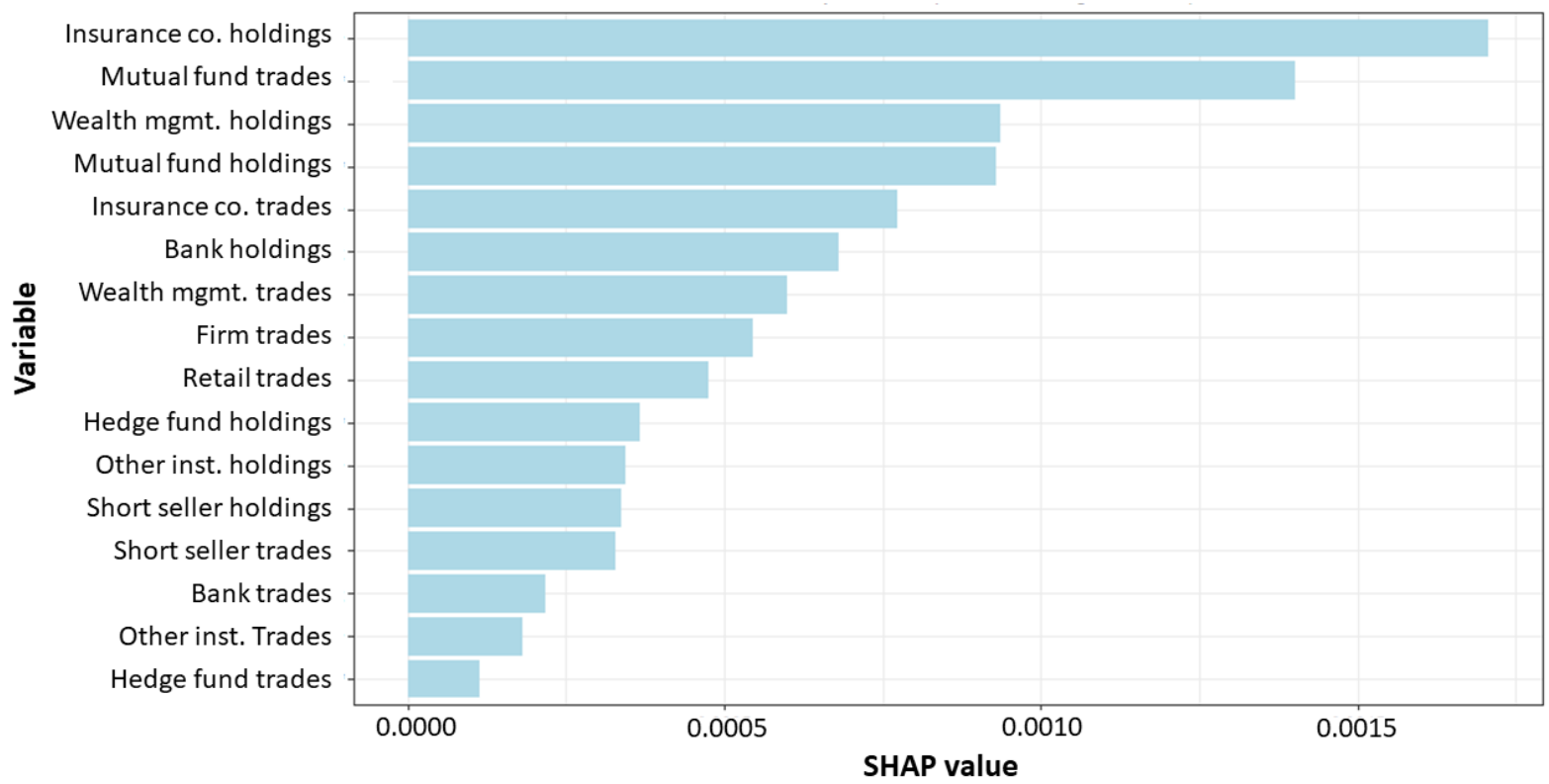
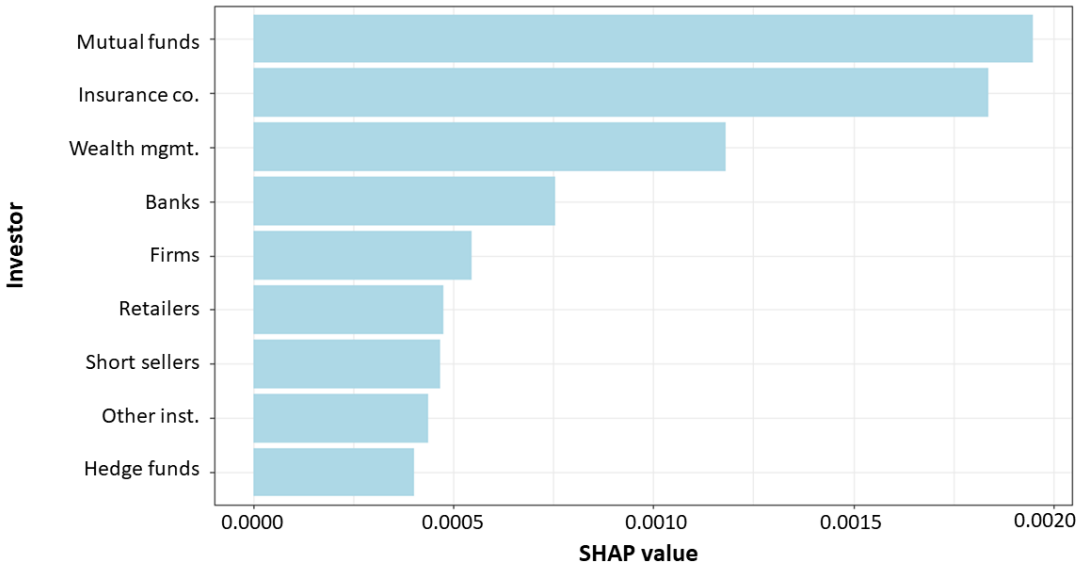


Figure 3. Investor and trades-versus-holdings importance

This figure illustrates the importance of each investor type and that of trades versus holdings for random forest. Panel A graphs the importance of each of the nine investor types estimated as the average absolute value of the sum of the SHAP values for the trading and holding variables corresponding to each investor. Panel B graphs the importance of trading versus holding variables measured as the average of the absolute value of the sum of the SHAP values for all trading or holding variables. We estimate importance for the last estimation window, which spans December 2015 to November 2020.

Panel A. Investor importance



Panel B. Trade versus holdings importance

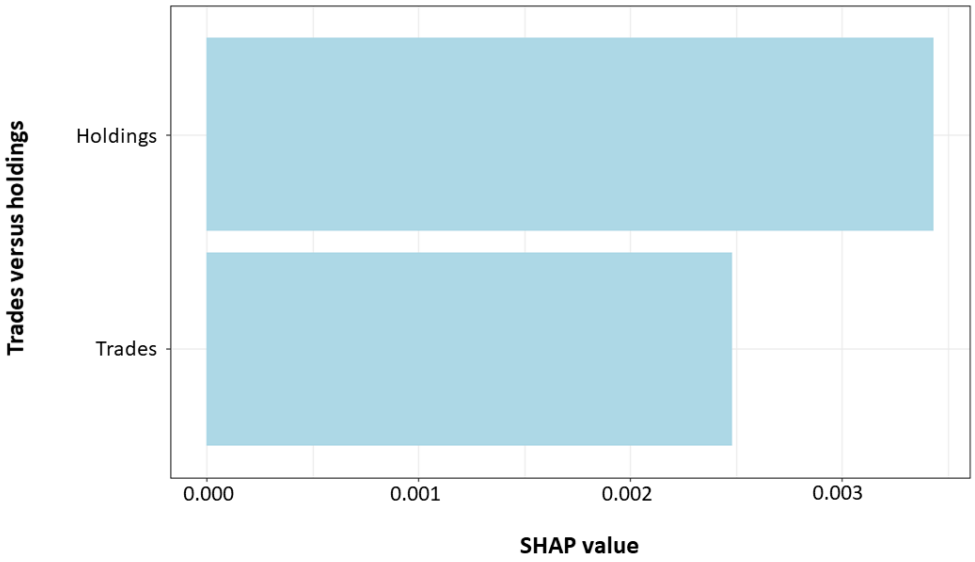


Figure 4. Variable importance: Beeswarm plot

This figure gives a beeswarm plot summarizing the impact of each variable on the random forest predictions. Each predicting variable is represented by a row in the beeswarm plot, and the sixteen variables are ordered by importance measured by their average absolute SHAP value. Each observation is represented by a single dot in each variable row, with its position on the horizontal axis given by the SHAP value of the variable for that observation. Dots "pile up" along each feature row to show density. Color is used to display the original value of a variable (feature value).

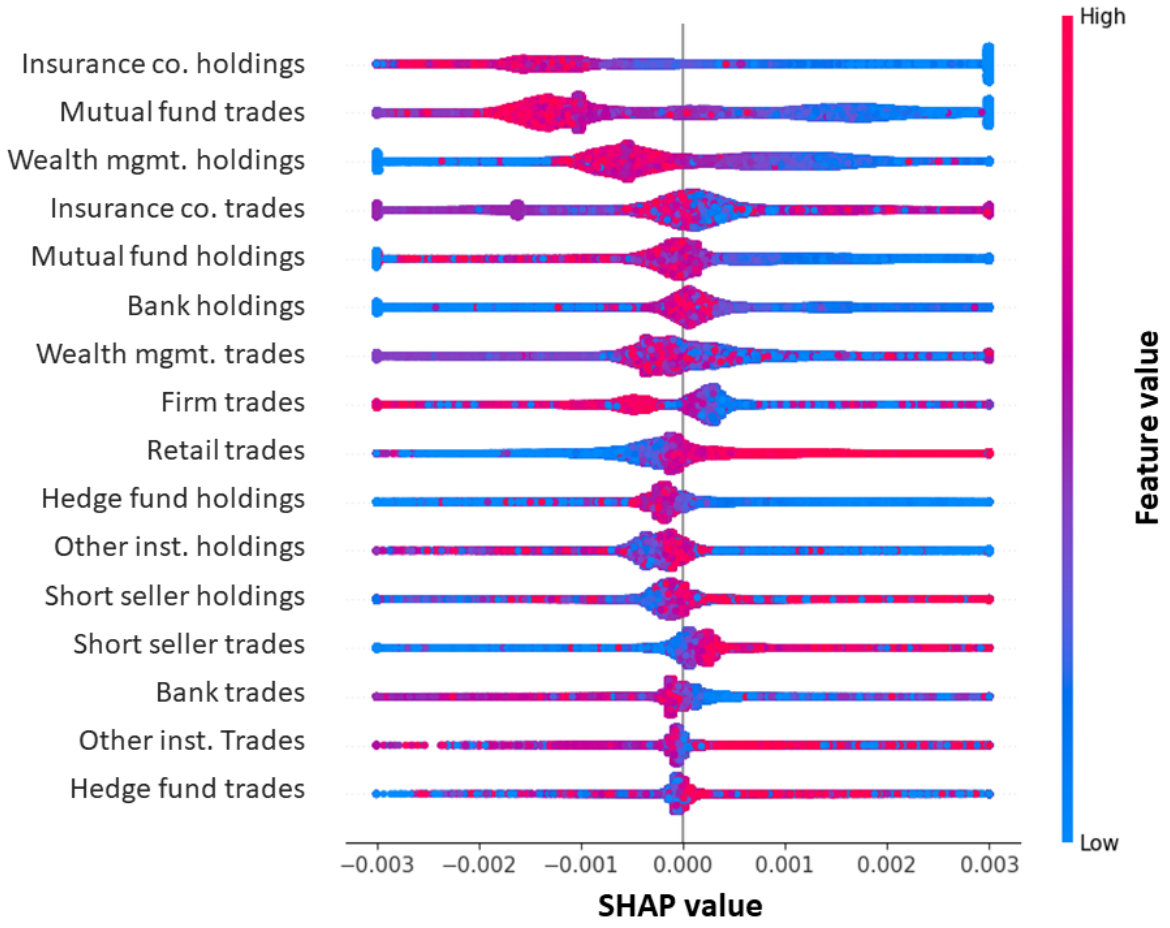


Figure 5. Interaction importance

This figure illustrates the importance of the top 20 interactions among pairs of variables. We estimate interaction importance by averaging the absolute SHAP interaction value across all observations within the last estimation window, which spans December 2015 to November 2020.

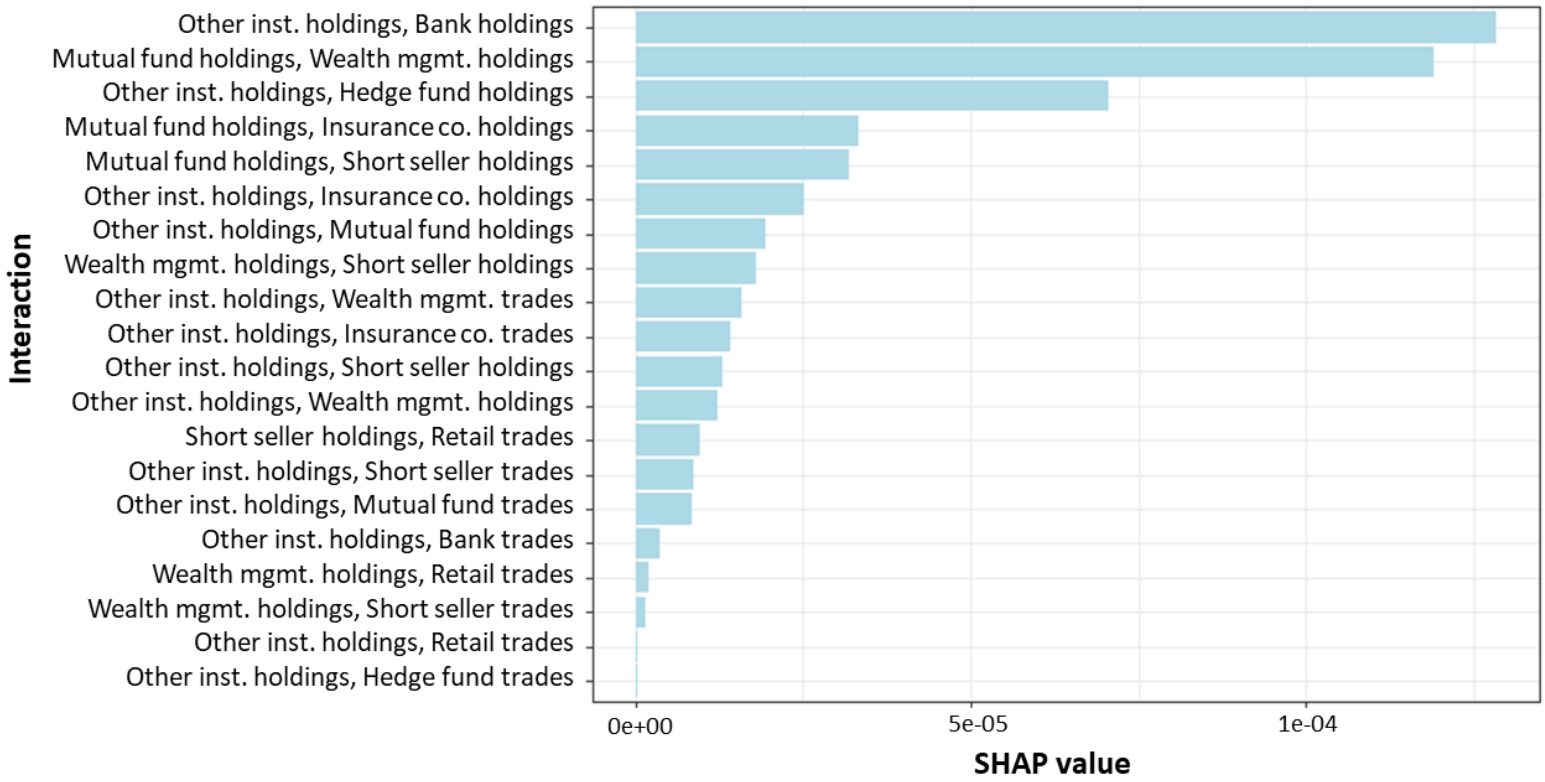
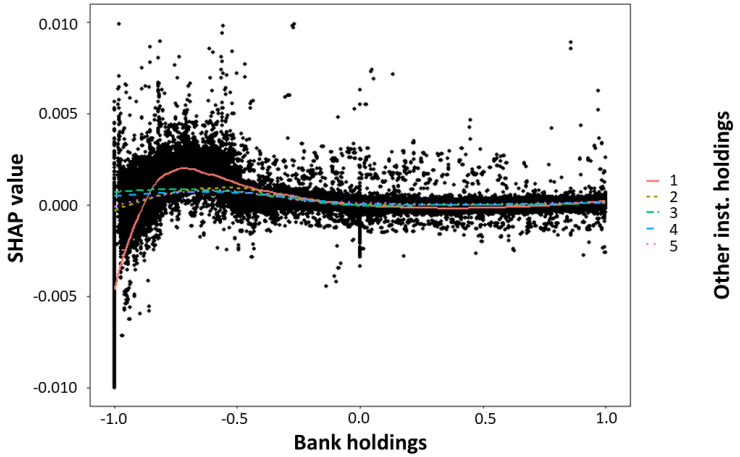


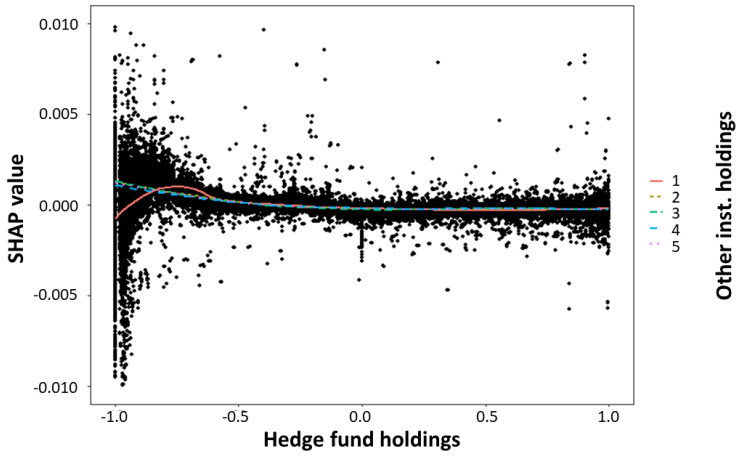
Figure 6. Top four interactions

This figures illustrates the four most important interactions, ranked by average absolute SHAP interaction value. Panel A depicts the interaction between bank holdings and other holdings, Panel B between hedge fund holdings and other holdings, Panel C between mutual fund holdings and insurance company holdings, and Panel D between mutual fund holdings and wealth management firm holdings. For each panel, the horizontal axis depicts the (standardized) first variable and the vertical axis its SHAP value for each observation (black dots). To visualize the interaction, we split all observations into quintiles of the second variable and depict, for each quintile, the conditional mean SHAP value of the first variable (solid lines). We compute SHAP values for the last estimation window, which spans the period from December 2015 to November 2020.

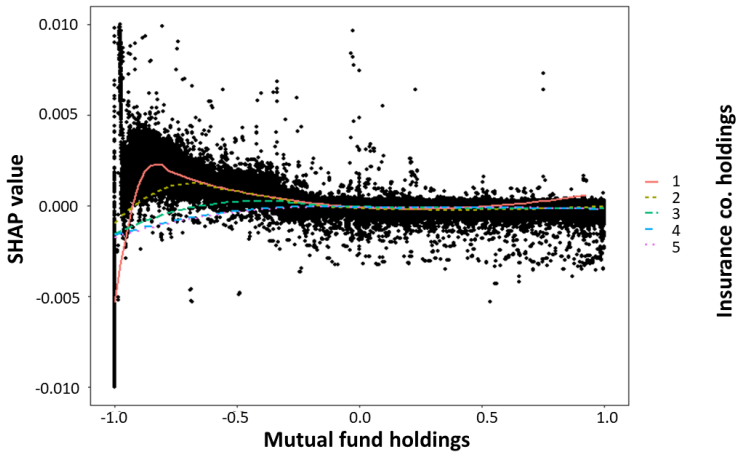
Panel A. Bank vs. other



Panel B. Hedge fund vs. other



Panel C. Mutual fund vs. insurance



Panel D. Mutual fund vs. wealth manag.

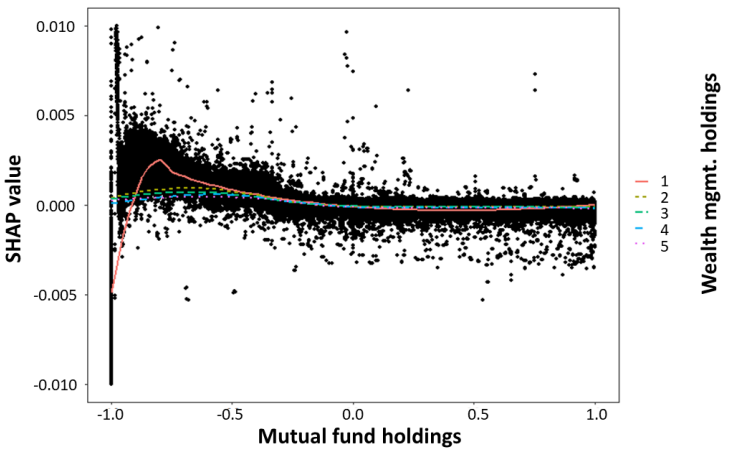
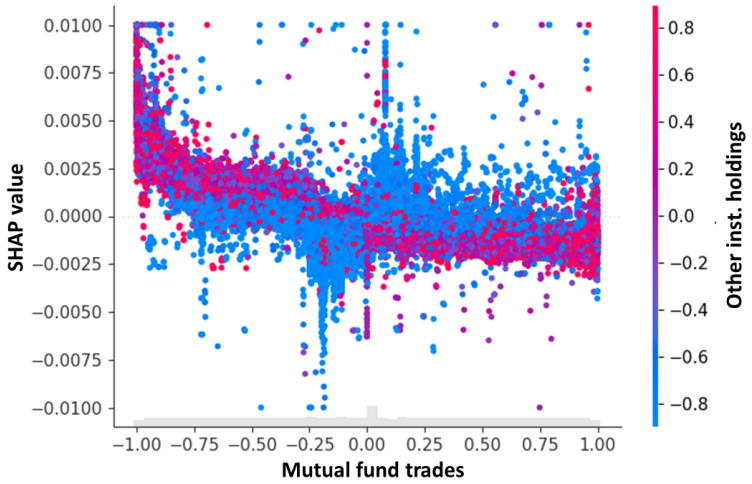


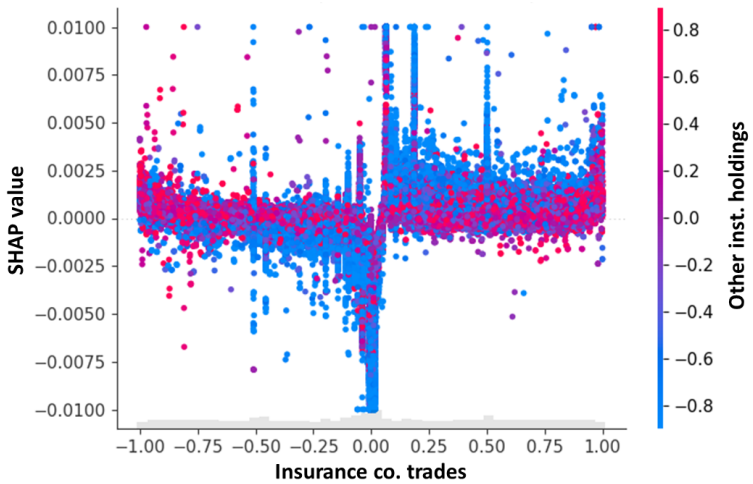
Figure 7. Interactions between trading variables and other institutional holdings

This figure illustrates the interactions between the trades of three types of institutions and the holdings of "other" institutions. Panel A depicts the interaction between mutual fund trades and other institutions holdings, Panel B between insurance company trades and other institutions holdings, and Panel C between wealth management trades and other institutions holdings. For each panel, the horizontal axis depicts the (standardized) trading variable and the vertical axis its SHAP value for each observation (dots). To visualize the interaction, we use color to display the original value of the other institutions holdings variable (red for high value and blue for low value). We compute SHAP values for the last estimation window, which spans December 2015 to November 2020.

Panel A. Mutual fund trades vs. other inst. holdings



Panel B. Insurance co. trades vs. other inst. holdings



Panel C. Wealth mgmt. trades vs. other inst. holdings

Table 1. Summary statistics

This table provides summary statistics (mean, median, standard deviation, and 10th and 90th percentiles) estimated at the stock-month panel-data level for holdings, trades, and the linear (LCP) and nonlinear (NLCP) composite predictors, for our out-os-sample period from January 2013 to December 2020. We consider nine market participants: banks, firms, hedge funds, insurance companies, mutual funds, other institutions, short sellers, wealth management firms, and retail investors. For firms and retail investors, we consider only trades because we lack information about holdings. We follow McLean et al. (2022) to construct all quarterly trades and quarterly holdings except retail trades, which we construct like Barber et al. (2024). We use a five-year rolling-window approach to train the six linear and six nonlinear prediction models described in Section 2.2 to predict next month's stock excess returns, using quarterly trades and lagged quarterly holdings of nine market participants as predicting variables. The LCP and NLCP are the average predictors across the six linear and six nonlinear models.

Variable	Mean	Median	St.Dev	p10	p90
Panel A: Holdings					
Bank	6.60%	5.54%	5.97%	0.01%	14.66%
Hedge fund	9.52%	8.12%	8.14%	0.40%	20.00%
Insurance co.	1.97%	1.36%	2.33%	0.00%	4.81%
Mutual fund	19.99%	19.94%	14.78%	0.28%	39.96%
Other inst.	20.06%	19.39%	14.78%	1.47%	37.62%
Short seller	-15.46%	-9.20%	20.23%	-37.97%	-0.49%
Wealth mgmt.	2.93%	1.79%	3.33%	0.00%	7.88%
Panel B: Trades					
Bank	-0.05%	0.00%	1.90%	-1.39%	1.38%
Hedge fund	0.02%	0.00%	3.14%	-2.21%	2.29%
Insurance co.	-0.01%	0.00%	0.85%	-0.50%	0.48%
Mutual fund	0.22%	0.02%	3.60%	-2.86%	3.52%
Other inst.	-0.14%	-0.05%	10.76%	-5.10%	4.78%
Short seller	-0.12%	0.01%	14.11%	-5.24%	4.85%
Wealth mgmt.	0.03%	0.00%	1.01%	-0.35%	0.46%
Firm	-1.60%	-0.08%	11.33%	-2.32%	0.98%
Retail	-2.61%	-1.49%	13.41%	-16.69%	9.87%
Panel C: Composite predictors					
LCP	0.63%	0.62%	0.58%	-0.10%	1.36%
NLCP	1.22%	1.17%	0.83%	0.35%	2.23%

Table 2. Alpha of univariate portfolios of stocks sorted by trades or lagged holdings

This table reports the alpha of univariate portfolios obtained by sorting stocks based on the trades (or lagged holdings) of a single type of market participant. Panels A and B report the results for the univariate portfolios constructed using trades and lagged holdings, respectively. For each panel, the first column reports the name of the sorting variable, the second to seventh columns report the alpha of the low, second, third, eighth, ninth, and high decile portfolios, respectively, and the eighth column reports the alpha for the long-short portfolio, which goes long stocks in the high decile and short stocks in the low decile. At the end of each month, we rank all sample stocks based on either the trades or the lagged holdings of each market participant and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile portfolio, as well as on the long-short portfolio, and report their alphas with respect to the five Fama and French (2015) and momentum factors. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. To facilitate the comparison, we evaluate performance in the period from 2013 to 2020, which coincides with the out-of-sample period for the evaluation of the composite return predictors.

	L	2	3	8	9	H	**H - L**
Panel A: Trade sorts							
Banks	0.17%	0.11%	0.15%	0.02%	-0.07%	-0.34%**	-0.5%***
	(1.13)	(0.88)	(1.18)	(0.17)	(-0.70)	(-2.33)	(-2.74)
Firms	-0.39%	-0.14%	0.31%**	0.13%	0.28%***	0.00%	0.39%
	(-1.20)	(-0.82)	(2.36)	(0.65)	(3.23)	(0.00)	(1.25)
Hedge funds	-0.21%	-0.08%	0.10%	0.08%	0.16%	0.16%	0.37%**
	(-1.51)	(-0.62)	(0.76)	(0.69)	(1.57)	(1.04)	(2.49)
Insurance co.	0.14%	0.10%	0.13%	-0.10%	-0.10%	-0.09%	-0.23%*
	(1.30)	(0.82)	(0.94)	(-0.77)	(-1.37)	(-0.91)	(-1.67)
Mutual funds	0.26%**	0.16%	0.24%**	-0.12%	-0.20%*	-0.13%	-0.39%**
	(2.07)	(0.90)	(2.23)	(-1.03)	(-1.87)	(-1.00)	(-2.07)
Other inst.	-0.09%	0.08%	-0.07%	0.16%	0.07%	0.29%*	0.37%***
	(-0.51)	(0.76)	(-0.56)	(1.04)	(0.64)	(1.81)	(2.69)
Short sellers	-0.66%***	-0.16%	0.01%	0.29%**	-0.17%	-0.45%**	0.21%
	(-2.91)	(-0.92)	(0.07)	(2.18)	(-1.14)	(-2.56)	(0.87)
Wealth mgmt.	0.18%	0.17%	0.33%**	0.14%	-0.05%	-0.12%	-0.30%*
	(1.14)	(1.64)	(2.49)	(1.08)	(-0.41)	(-0.81)	(-1.80)
Retail	0.14%	0.23%**	0.01%	-0.26%	-0.04%	0.62%***	0.48%**
	(1.32)	(2.00)	(0.06)	(-1.35)	(-0.21)	(3.02)	(2.17)
Panel B: Lagged-holdings sorts							
Banks	-0.41%	0.31%	0.60%**	-0.10%	0.08%	-0.13%	0.27%
	(-0.99)	(0.93)	(2.21)	(-1.34)	(1.11)	(-1.44)	(0.67)
Hedge funds	-0.54%	0.40%*	0.16%	0.13%	0.09%	-0.02%	0.52%
	(-1.43)	(1.76)	(1.04)	(1.06)	(0.95)	(-0.15)	(1.44)
Insurance co.	0.25%	-0.09%	0.45%	-0.08%	0.00%	-0.07%	-0.32%
	(0.69)	(-0.25)	(1.53)	(-1.18)	(0.01)	(-0.85)	(-0.93)
Mutual funds	-0.78%*	0.74%**	0.48%**	-0.01%	-0.09%	-0.10%	0.69%
	(-1.73)	(2.40)	(2.30)	(-0.06)	(-1.14)	(-1.01)	(1.42)
Other inst.	-0.47%	0.37%*	0.15%	0.01%	0.15%	-0.05%	0.42%
	(-1.11)	(1.84)	(1.01)	(0.14)	(1.62)	(-0.35)	(1.14)
Short sellers	-0.47%**	-0.37%**	-0.42%***	0.24%**	0.33%	1.04%***	1.51%***
	(-2.16)	(-2.15)	(-2.89)	(2.29)	(1.46)	(4.03)	(5.17)
Wealth mgmt.	-0.47%	0.16%	0.26%**	0.01%	0.11%	0.11%	0.58%
	(-1.06)	(0.52)	(2.09)	(0.14)	(0.94)	(0.93)	(1.35)

Table 3. Alpha of portfolios based on composite return predictors

This table reports the alpha of the portfolios of stocks sorted by the linear (LCP) and nonlinear (NLCP) composite return predictors. The first column reports the label for each decile portfolio and the long-short portfolio, the second and third columns report the alpha of each portfolio based on the LCP with respect to the five Fama and French (2015) and momentum factors (FF5+MOM) and the five Hou et al. (2021) and momentum factors (q5+MOM), the fourth and fifth columns for the portfolios based on the NLCP, and the sixth and seventh columns for the difference between the returns of the portfolios based on NLCP and LCP (NLCP minus LCP). At the end of each month, we rank all sample stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile portfolio, as well as on the long-short portfolio, and report their alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	LCP		NLCP		NLCP minus LCP	
	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM
L	-0.98%***	-0.48%*	-1.49%***	-1.00%**	-0.51%***	-0.51%**
	(-3.72)	(-1.93)	(-4.11)	(-2.49)	(-2.69)	(-2.22)
2	-0.36%**	-0.01%	-0.06%	0.29%	0.30%*	0.30%*
	(-2.06)	(-0.03)	(-0.35)	(1.56)	(1.71)	(1.76)
3	-0.13%	0.17%	0.03%	0.31%*	0.16%	0.14%
	(-0.73)	(0.95)	(0.22)	(1.97)	(1.11)	(0.99)
4	0.23%	0.53%**	-0.02%	0.28%**	-0.24%	-0.25%
	(1.28)	(2.51)	(-0.16)	(2.15)	(-1.54)	(-1.37)
5	0.12%	0.35%**	0.09%	0.31%**	-0.03%	-0.03%
	(0.95)	(2.16)	(0.56)	(2.24)	(-0.16)	(-0.17)
6	0.29%**	0.55%***	0.12%	0.42%**	-0.17%	-0.13%
	(2.14)	(3.65)	(0.90)	(2.33)	(-1.15)	(-0.76)
7	0.34%***	0.53%***	0.03%	0.31%*	-0.31%**	-0.22%**
	(2.76)	(4.08)	(0.22)	(1.78)	(-2.19)	(-2.01)
8	0.32%**	0.55%***	0.43%***	0.68%***	0.12%	0.13%
	(2.06)	(4.54)	(3.12)	(4.07)	(1.01)	(1.00)
9	0.39%***	0.73%***	0.63%***	0.91%***	0.24%	0.18%
	(3.32)	(5.77)	(3.57)	(5.31)	(1.57)	(1.36)
H	0.80%***	1.20%***	1.25%***	1.61%***	0.45%*	0.41%
	(3.77)	(5.52)	(4.87)	(5.71)	(1.95)	(1.62)
H-L	1.78%***	1.68%***	2.74%***	2.60%***	0.96%***	0.92%***
	(10.03)	(6.01)	(9.80)	(7.60)	(3.46)	(2.65)

Table 4. Alpha of returns net of transaction costs of LCP and NLCP long-short portfolios

This table reports the alpha of the returns of the long-short portfolio of stocks sorted by the linear and nonlinear composite predictors, as well as the alpha of the difference between the returns of the NLCP and LCP long-short portfolios in the absence of transaction costs (0bps) and in the presence of proportional transaction costs of 30 and 60 basis points (30bps and 60bps). The first column reports the level of transaction costs, the second and third columns report the alpha of the LCP long-short portfolio with respect to the five Fama and French (2015) and momentum factors (FF5+MOM) and the five Hou et al. (2021) and momentum factors (q5+MOM), the fourth and fifth columns for the NLCP long-short portfolio, and the sixth and seventh columns for the difference between the returns of the NLCP and LCP long-short portfolios (NLCP minus LCP). At the end of each month, we rank all sample stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile as well as on the long-short portfolio and report the alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	LCP		NLCP		NLCP minus LCP	
	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM
0bps	1.78%***	1.68%***	2.74%***	2.60%***	0.96%***	0.92%***
30bps	1.51%***	1.40%***	2.31%***	2.16%***	0.79%***	0.76%**
60bps	1.25%***	1.12%***	1.88%***	1.72%***	0.63%**	0.60%*

Table 5. Persistence of alpha of long-short portfolios based on composite return predictors

This table reports the monthly alpha of the long-short portfolios of stocks sorted by LCP and NLCP, for specific months after portfolio formation, ranging from the first month to the 24th month after portfolio formation. The first column reports the number of the month following portfolio formation. The second and third columns report the FF5+MOM and q5+MOM alphas of the LCP long-short portfolio, the fourth and fifth columns for the NLCP long-short portfolio, and the sixth and seventh columns for the difference between the returns of the NLCP and LCP long-short portfolios (NLCP minus LCP). At the end of each month, we rank all sample stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted excess returns on the long-short portfolio, for up to 24 months after portfolio formation, and report the alphas for each month separately. We compute Newey-West adjusted t-statistics and use ***, **, and * to indicate statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	LCP		NLCP		NLCP minus LCP	
	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM
m + 1	1.76%***	1.67%***	2.74%***	2.60%***	0.98%***	0.93%***
m + 2	1.59%***	1.43%***	2.28%***	2.11%***	0.69%***	0.68%**
m + 3	1.46%***	1.25%***	1.85%***	1.69%***	0.39%	0.44%
m + 4	1.43%***	1.23%***	1.85%***	1.65%***	0.42%	0.42%
m + 5	1.55%***	1.36%***	1.60%***	1.52%***	0.04%	0.16%
m + 6	1.31%***	1.10%***	1.56%***	1.60%***	0.25%	0.50%*
m + 7	1.55%***	1.39%***	1.86%***	1.88%***	0.31%	0.50%*
m + 8	1.35%***	1.11%**	1.81%***	1.78%***	0.46%*	0.67%***
m + 9	1.29%***	1.06%**	1.78%***	1.69%***	0.49%**	0.63%**
m + 10	0.97%***	0.73%*	1.88%***	1.92%***	0.91%***	1.18%***
m + 11	0.97%***	0.86%**	1.51%***	1.52%***	0.55%*	0.66%**
m + 12	0.84%**	0.62%	1.28%***	1.37%***	0.44%	0.75%**
m + 13	1.06%***	0.85%**	1.19%***	1.23%***	0.13%	0.38%
m + 14	0.95%***	0.62%	1.01%**	0.96%**	0.06%	0.33%
m + 15	0.79%**	0.46%	1.42%***	1.20%**	0.63%***	0.73%***
m + 16	0.80%**	0.45%	1.22%***	0.98%**	0.42%*	0.53%*
m + 17	0.75%**	0.42%	0.78%*	0.64%	0.03%	0.22%
m + 18	0.81%**	0.52%	0.97%*	0.87%	0.15%	0.34%
m + 19	0.77%*	0.49%	1.36%***	1.21%**	0.58%**	0.72%**
m + 20	0.64%*	0.33%	1.18%**	1.05%*	0.54%*	0.71%**
m + 21	0.59%	0.39%	1.04%**	0.97%*	0.45%	0.58%**
m + 22	0.63%*	0.42%	0.63%	0.54%	0.00%	0.12%
m + 23	0.66%*	0.49%	0.90%*	0.89%	0.24%	0.40%
m + 24	0.72%*	0.55%	1.09%***	1.07%**	0.37%	0.52%

Table 6. Fama-MacBeth regressions of monthly returns

This table reports the results for the Fama and MacBeth (1973) regressions of monthly stock returns on the LCP and NLCP indicator variables controlling for common firm characteristics. Each month, we sort sample stocks into decile portfolios based on their LCP and NLCP values. We then construct the indicator variables, I_LCP or I_NLCP, by setting them to one if the corresponding LCP or NLCP value falls within the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of stock returns on the indicator variables controlling for the following firm characteristics: firm size (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), asset growth (AG), gross profitability (GP), turnover (TO), and idiosyncratic volatility (IVOL). We winsorize characteristics at the 1st and 99th percentiles and standardize them to have zero mean and unit standard deviation. The first column reports the symbol of each explanatory variable, the second, third, and fourth columns report the results for the regressions that include only the I_LCP indicator variable, only the I_NLCP indicator variable, and both the I_LCP and I_NLCP indicator variables, respectively. We run the regressions for the period from 2013 to 2020, which coincides with the out-of-sample period we use to evaluate portfolio performance. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The coefficients are reported in percentage.

Variable	Ret	Ret	Ret
I_LCP	0.3233***		0.0006
	(3.02)		(0.01)
I_NLCP		0.7701***	0.7798***
		(5.03)	(4.77)
SIZE	-0.2483**	-0.2376*	-0.2312*
	(-2.05)	(-1.96)	(-1.93)
BM	-0.1462	-0.1551	-0.1574
	(-1.11)	(-1.17)	(-1.18)
MOM	-0.2008	-0.2124*	-0.2120*
	(-1.60)	(-1.68)	(-1.69)
STR	-0.2794***	-0.3019***	-0.2992***
	(-3.15)	(-3.41)	(-3.38)
AG	-0.0685	-0.0635	-0.0617
	(-1.11)	(-1.04)	(-1.01)
GP	0.1145	0.0989	0.0978
	(1.10)	(0.95)	(0.94)
TO	-1.1789***	-1.1399***	-1.1409***
	(-7.01)	(-6.79)	(-6.77)
IVOL	0.4563**	0.4592**	0.4604**
	(2.54)	(2.55)	(2.58)
Obs.	230,862	230,862	230,862
R-squared	0.04	0.04	0.04

Table 7. Fama-MacBeth regressions: interactions with firm size

This table reports the results for the Fama and MacBeth (1973) regressions of monthly stock returns on the LCP and NLCP indicator variables after including interaction between firm size and the LCP and NLCP indicator variables. Each month, we sort sample stocks into decile portfolios based on their LCP and NLCP values. We then construct the indicator variables, I_LCP or I_NLCP, by setting them to one if the corresponding LCP or NLCP value falls within the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of stock returns on the indicator variables and their interaction terms with firm size, while also controlling for the following firm characteristics: firm size (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), asset growth (AG), gross profitability (GP), turnover (TO), and idiosyncratic volatility (IVOL). We winsorize characteristics at the 1st and 99th percentiles and standardize them to have zero mean and unit standard deviation. The first column reports the symbol of each explanatory variable, the second, third, and fourth columns report the results for the regressions that include the I_LCP indicator variable and its interaction term with size, the I_NLCP indicator variable and its interaction term with size, and both the I_LCP and I_NLCP indicator variables and their interaction terms with size, respectively. We run the regressions for the period from 2013 to 2020, which coincides with the out-of-sample period we use to evaluate portfolio performance. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The coefficients are reported in percentage.

Variable	Ret	Ret	Ret
I_LCP	0.3220***		0.0278
	(3.21)		(0.26)
I_LCP * SIZE	-0.0765		0.1881
	(-0.58)		(1.11)
I_NLCP		0.6119***	0.5963***
		(4.77)	(4.97)
I_NLCP * SIZE		-0.3242**	-0.4166**
		(-2.60)	(-2.52)
SIZE	-0.2471**	-0.2291*	-0.2299*
	(-2.00)	(-1.89)	(-1.88)
BM	-0.1472	-0.1621	-0.1612
	(-1.13)	(-1.21)	(-1.20)
MOM	-0.1985	-0.2162*	-0.2109*
	(-1.59)	(-1.69)	(-1.67)
STR	-0.2788***	-0.3068***	-0.3012***
	(-3.17)	(-3.47)	(-3.42)
AG	-0.0685	-0.0614	-0.0588
	(-1.10)	(-1.01)	(-0.96)
GP	0.1122	0.0896	0.0908
	(1.08)	(0.86)	(0.87)
TO	-1.1801***	-1.1261***	-1.1353***
	(-6.95)	(-6.77)	(-6.74)
IVOL	0.4563**	0.4587**	0.4570**
	(2.53)	(2.53)	(2.55)
Obs.	230,862	230,862	230,862
R-squared	0.04	0.05	0.05

Table 8. Trading- and holdings-based predictors

This table reports the results for the Fama and MacBeth (1973) regressions of monthly stock returns on indicator variables obtained using the LCP and NLCP based on only the combined trades (LCP_Trading and NLCP_Trading) or only the lagged combined holdings (LCP_Holding and NLCP_Holding) of all market participants. The indicator variables are equal to one if the composite predictor is in the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of next-month stock returns on the indicator variables controlling for the following firm characteristics: firm size (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), asset growth (AG), gross profitability (GP), turnover (TO), and idiosyncratic volatility (IVOL). We winsorize characteristics at the 1st and 99th percentiles and standardize them to have zero mean and unit standard deviation. The first column reports the symbol of each explanatory variable, the second third, fourth, and fifth columns report the results for the regressions that include (individually) the LCP_Trading, LCP_Holding, NLCP_Trading, or NLCP_Holding indicator variables, respectively, and the sixth column for the regression that includes all four indicator variables. We run the regressions for the period from 2013 to 2020, which coincides with the out-of-sample period we use to evaluate portfolio performance. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The coefficients are reported in percentage.

Variable	Ret	Ret	Ret	Ret	Ret
I_LCP_Trading	0.2125**				0.1254
	(2.12)				(1.07)
I_LCP_Holding		0.3261**			0.0962
		(2.46)			(0.96)
I_NLCP_Trading			0.4262***		0.3187**
			(3.17)		(2.21)
I_NLCP_Holding				0.5813***	0.4617***
				(3.66)	(3.20)
SIZE	-0.2823**	-0.2484**	-0.2898**	-0.2223*	-0.2547**
	(-2.32)	(-2.01)	(-2.45)	(-1.82)	(-2.14)
BM	-0.1411	-0.1452	-0.1446	-0.1475	-0.1536
	(-1.08)	(-1.11)	(-1.10)	(-1.11)	(-1.15)
MOM	-0.1822	-0.2158*	-0.1855	-0.2287*	-0.2122
	(-1.44)	(-1.68)	(-1.46)	(-1.79)	(-1.64)
STR	-0.2810***	-0.2773***	-0.2872***	-0.2830***	-0.2880***
	(-3.15)	(-3.12)	(-3.21)	(-3.22)	(-3.29)
AG	-0.0767	-0.0708	-0.0729	-0.0705	-0.0625
	(-1.23)	(-1.16)	(-1.17)	(-1.15)	(-1.04)
GP	0.1219	0.1092	0.1154	0.0953	0.0871
	(1.17)	(1.05)	(1.09)	(0.91)	(0.83)
TO	-1.1910***	-1.1694***	-1.1689***	-1.1533***	-1.1365***
	(-7.11)	(-6.95)	(-7.06)	(-6.81)	(-6.74)
IVOL	0.4347**	0.4636**	0.4542**	0.4646***	0.4796***
	(2.40)	(2.58)	(2.48)	(2.64)	(2.75)
Obs.	230,862	230,862	230,862	230,862	230,862
R-squared	0.04	0.04	0.04	0.04	0.05

Table 9. Portfolio performance and firm size

This table reports the alpha of the portfolios of stocks sorted by the LCP (or NLCP) across sub-samples of stocks categorized by firm size. At the end of each month, we rank all sample stocks based on firm size and sort them into tercile portfolios. We then rank stocks within each tercile based on either the LCP or NLCP, and sort them into decile portfolios. We then compute the equal-weighted returns on each decile as well as on the long-short portfolio and report the alphas with respect to the five Fama and French (2015) and momentum factors (FF5+MOM). The first column reports the label for each decile portfolio and the long-short portfolio, the second and third columns report the alphas for small firms, the fourth and fifth columns for medium firms, and the last two columns for large firms. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	Small		Medium		Large	
	LCP	NLCP	LCP	NLCP	LCP	NLCP
L	-2.02%***	-2.39%***	-0.61%**	-1.00%***	-0.39%**	-0.29%**
	(-3.31)	(-3.79)	(-2.54)	(-4.03)	(-2.55)	(-2.05)
2	-0.61%	-0.87%*	-0.18%	-0.13%	-0.16%	-0.32%*
	(-1.32)	(-1.66)	(-1.07)	(-0.92)	(-1.22)	(-1.95)
3	0.17%	0.28%	-0.14%	0.34%**	0.14%	0.01%
	(0.38)	(0.88)	(-0.75)	(2.32)	(1.08)	(0.06)
4	0.68%*	0.43%	-0.04%	0.12%	-0.25%**	-0.11%
	(1.77)	(1.47)	(-0.34)	(0.88)	(-2.06)	(-0.94)
5	0.93%***	0.47%	0.08%	-0.18%	0.12%	0.02%
	(3.13)	(1.62)	(0.62)	(-1.16)	(0.91)	(0.14)
6	0.90%***	0.59%**	0.17%	0.36%	-0.12%	0.00%
	(3.50)	(2.11)	(0.96)	(1.56)	(-1.07)	(0.03)
7	0.75%**	0.70%**	0.04%	-0.22%	0.04%	-0.01%
	(2.01)	(2.39)	(0.21)	(-1.50)	(0.50)	(-0.22)
8	0.92%**	1.20%***	0.28%*	0.02%	-0.24%***	0.02%
	(2.39)	(2.92)	(1.86)	(0.12)	(-4.95)	(0.50)
9	0.67%**	1.95%***	0.05%	0.45%***	-0.07%	0.04%
	(2.39)	(5.07)	(0.41)	(3.52)	(-0.69)	(0.42)
H	1.25%***	1.28%***	0.42%*	0.29%	0.26%***	-0.02%
	(3.04)	(3.14)	(1.86)	(1.53)	(3.13)	(-0.22)
H-L	3.27%***	3.68%***	1.03%***	1.29%***	0.65%***	0.26%*
	(8.55)	(7.03)	(3.44)	(5.28)	(3.39)	(1.82)

Table 10. Effect of information environment

This table reports the results for Fama and MacBeth (1973) regressions for sub-samples of stocks categorized based on five firm characteristics that proxy information asymmetry: firm age, idiosyncratic volatility, illiquidity, analyst coverage, and analyst disagreement. Firm age is the number of years since the firm was first covered by CRSP, idiosyncratic volatility as the standard deviation of the residuals from regressing daily excess stock returns on the three-factor Fama and French (1992) model over the previous six months, illiquidity is the measure of Amihud (2002), analyst coverage as the number of analysts with valid earnings per share forecast as of prior month-end, and analyst disagreement as analyst forecast dispersion (standard deviation of analyst forecasts divided by absolute value of average analyst forecast in the prior month). Each month and within each stock sub-sample, we sort stocks into decile portfolios based on their LCP or NLCP values. We then construct the indicator variables, I_LCP or I_NLCP, by setting them to one if the corresponding LCP or NLCP value falls within the high decile, minus one if it is in the low decile, and zero otherwise. We then run monthly regressions of stock returns on I_LCP and I_NLCP, and the following firm characteristics: firm size (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), asset growth (AG), gross profitability (GP), turnover (TO), and idiosyncratic volatility (IVOL). We winsorize characteristics at the 1st and 99th percentiles and standardize them to have zero mean and unit standard deviation. The first column reports the symbol of each explanatory variable, the rest of the columns report the regression results for each stock sub-sample. We run the regressions for the period from 2013 to 2020, which coincides with the out-of-sample period we use to evaluate portfolio performance. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The coefficients are reported in percentage.

	Firm age		Idio. vol.		Illiquidity		Analyst coverage		Analyst disagreement	
	Young	Old	Low	High	Low	High	Low	High	Low	High
	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret
I_LCP	0.066	-0.056	-0.027	-0.199	-0.007	-0.025	-0.213	0.145	0.024	-0.025
	(0.37)	(-0.42)	(-0.26)	(-0.91)	(-0.08)	(-0.11)	(-0.99)	(1.39)	(0.17)	(-0.19)
I_NLCP	0.801***	0.807***	0.317***	1.005***	0.239*	0.879***	0.996***	0.181	0.430**	0.687***
	(4.02)	(3.67)	(2.71)	(4.09)	(1.84)	(4.45)	(4.41)	(1.14)	(2.62)	(2.82)
Character.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103,264	127,598	122,333	108,529	123,587	107,247	102,829	94,004	83,219	78,427
R-squared	0.05	0.05	0.05	0.05	0.08	0.05	0.05	0.10	0.06	0.08

Table 11. Predicting operating performance and earnings announcement returns

This table reports the results for the Fama and MacBeth (1973) regressions of future operating performance and earning announcement returns on the indicator variables I_LCP and I_NLCP, controlling for firm characteristics and current measures of operating performance. We use four measures of operating performance: cash flows (CF), which is the difference between income before extraordinary items and total accruals, divided by total assets, gross margin (GM), which is is sales minus cost of goods sold scaled by current sales, return-on-equity (ROE), which is the sum of income before extraordinary items and interest expenses, divided by the lagged total equity, and return-on-asset (ROA), which is the sum of income before extraordinary items and interest expenses, divided by the lagged total assets. Earnings announcement returns (CAR) are cumulative abnormal returns in the $[-1, 1]$ three-day window around the earnings announcement day, where abnormal returns are the difference between the daily stock return and that of the corresponding portfolio among the six size and book-to-market Fama-French portfolios. We then run monthly regressions of the four measures of future operating performance and earnings announcement returns on I_LCP or I_NLCP, the firm characteristics defined in Section 3.3, and current measures of operating performance (CF0, GM0, ROE0, ROA0). We run the regressions for the period from 2013 to 2020, which coincides with the out-of-sample period we use to evaluate portfolio performance. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The coefficients for the four measures of operating performance and earnings announcement returns reported in percentage.

Variable	CF	CF	GM	GM	ROE	ROE	ROA	ROA	CAR	CAR
I_LCP	0.476***		0.263**		0.487		0.493**		0.06	
	(3.70)		(2.35)		(1.52)		(2.53)		(0.72)	
I_NLCP		0.457***		0.253**		0.777***		0.626**		0.28***
		(6.09)		(2.78)		(3.30)		(2.10)		(3.39)
CF0	33.186***	33.181***								
	(90.62)	(91.98)								
GM0			45.488***	45.484***						
			(372.73)	(374.20)						
ROE0					67.562***	67.537***				
					(49.59)	(49.65)				
ROA0							44.324***	44.307***		
							(17.57)	(17.55)		
Character.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	70,648	70,648	75,254	75,254	73,419	73,419	68,130	68,130	203,949	203,949
R-squared	0.91	0.91	0.96	0.96	0.91	0.91	0.89	0.89	0.01	0.01

Table 12. Average anomalies for portfolios of stocks sorted by composite return predictors

Panels A and B of this table report the average of each stock anomaly for the portfolios of stocks sorted by the LCP and NLCP. For each panel, the first column reports the name of the anomalies, the second to eighth columns report the averaged anomaly value of the low, second, third, eighth, ninth, high decile portfolios, and the long-short portfolio, respectively. The last column reports the t-statistics for the long-short portfolio anomalies. At the end of each month, we rank all sample stocks based on either the LCP or NLCP and then sort them into decile portfolios. We then compute the time-series average of the cross-sectional means of each stock anomaly on each decile as well as on the long-short portfolio. Out of the 102 anomalies documented in Green et al. (2017), we select 12 anomalies whose return is significant (t-stat >1.66) for our sample period from 2008 to 2020. For easier interpretation, we change the sign of anomalies whose return is negative, including market capitalization, idiosyncratic volatility, momentum_1m, and asset growth, so that the mean anomaly values for the LCP and NLCP long-short portfolios should be positive if they select stocks on the right side of the anomaly. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	L	2	3	8	9	H	H - L	t-stat
Panel A: Anomalies for the portfolios of stocks sorted by LCP								
(-) Market capitalization	12.858	13.420	13.613	13.778	13.536	13.107	0.25**	2.23
Book-to-market	0.423	0.441	0.457	0.534	0.551	0.609	0.19***	14.97
Gross margin	0.232	0.298	0.321	0.350	0.353	0.349	0.12***	10.80
Illiquidity	0.144	0.207	0.295	0.915	1.117	1.246	1.10***	8.60
(-) Idiosyncratic volatility	0.052	0.050	0.051	0.060	0.065	0.078	0.03***	13.33
Momentum_12m	0.019	0.061	0.092	0.100	0.098	0.068	0.05**	2.29
(-) Momentum_1m	0.017	0.016	0.014	0.008	0.005	-0.002	-0.02*	-1.98
(-) Asset growth	0.051	0.079	0.092	0.143	0.161	0.182	0.13***	16.84
Dividend yield	0.010	0.011	0.012	0.011	0.011	0.010	0.00	0.37
Analyst coverage	6.991	7.968	8.533	7.596	6.819	5.106	-1.89***	-6.82
Price delay	0.057	0.042	0.038	0.053	0.053	0.066	0.01	1.03
Combined fundamental	3.871	4.174	4.285	4.286	4.203	3.974	0.10*	1.90
Panel B: Anomalies for the portfolios of stocks sorted by NLCP								
(-) Market capitalization	12.078	13.086	13.733	14.003	13.641	12.330	0.25**	2.27
Book-to-market	0.492	0.474	0.458	0.499	0.565	0.676	0.18***	11.48
Gross margin	0.177	0.336	0.351	0.343	0.342	0.319	0.14***	16.27
Illiquidity	0.385	0.358	0.276	0.739	1.313	2.365	1.98***	8.10
(-) Idiosyncratic volatility	0.066	0.057	0.052	0.052	0.059	0.088	0.02***	12.13
Momentum_12m	-0.037	0.082	0.109	0.106	0.080	0.032	0.07***	2.65
(-) Momentum_1m	0.027	0.017	0.015	0.008	0.003	-0.013	-0.04***	-4.11
(-) Asset growth	0.056	0.091	0.103	0.138	0.157	0.147	0.09***	12.35
Dividend yield	0.009	0.011	0.011	0.011	0.011	0.012	0.00***	2.77
Analyst coverage	5.075	7.903	8.691	7.948	6.352	3.801	-1.27***	-4.81
Price delay	0.081	0.038	0.029	0.049	0.078	0.134	0.05***	5.05
Combined fundamental	3.514	4.260	4.439	4.297	4.072	3.632	0.12**	2.42

Table 13. Performance of factor models based on composite return predictors

This table reports the performance of several factor models in terms of their ability to explain anomaly returns and the Sharpe ratio generated by their factors. We consider four factor models: (i) the five Fama and French (2015) and momentum factors (FF5+MOM), (ii) the five Hou et al. (2021) and momentum factors (q5+MOM), (iii) a two-factor model including the market factor and the LCP factor defined as the return of the LCP equal-weighted long-short portfolio (LCP+MKT), and (iv) a two-factor model including the market factor and the NLCP factor defined as the return of the NLCP equal-weighted long-short portfolio (NLCP+MKT). Out of the 102 anomalies documented in Green et al. (2017), we select the 12 anomalies whose return is significant (t-stat >1.66) for our sample period from 2008 to 2020. We run time series regressions of the 12 anomaly returns on each of the four factor models. We run time series regressions of the returns of the 12 anomalies on each of the four factor models. The first and second rows in the table report the average (across the 12 anomalies) of the absolute value of the alpha and alpha t-stat. The third row in the table reports the annualized Sharpe ratio of the mean-variance portfolio of the factors in each model, and the fourth and fifth rows report the p-value for the difference between the Sharpe ratio of each model and that of the FF5+MOM and q5+MOM models.

	FF5+MOM	q5+MOM	LCP+MKT	NLCP+MKT
Average absolute alpha	0.59	0.44	0.46	0.50
Average absolute t-stat	2.03	1.41	1.19	1.16
Annualized Sharpe ratio (SR)	1.13	1.71	2.32	3.09
P-value of SR difference compared to FF5+MOM	NA	0.18	0.30	0.02
P-value of SR difference compared to q5+MOM	0.17	NA	0.55	0.05

Appendix A Trades & holdings and machine-learning tools

A.1 Trades and holdings of market participants

The predicting variables included in the training sample consist of both trades and lagged holdings from nine market participants. As detailed in Section 2.1, our analysis covers six types of institutions that report their holdings on SEC 13F form, along with other investors categories such as retail traders, short sellers, and firms.

We gather institutional holdings data from *Thomson/Refinitiv S12* and *13f*, following the approach outlined by McLean et al. (2022) to categorize institutions into six types. First, we combine mutual fund holdings reported in S12 form filings with their corresponding 13F form filings, treating the reported number of shares by mutual funds as their raw holdings. Second, we employ type codes developed by Brian Bushee (available at https://accounting-faculty.wharton.upenn.edu/bushee/) to identify and filter out institutions classified as banks or insurance companies, extracting their corresponding holdings. Third, we utilize the search scheme in McLean et al. (2022) to identify wealth management firms and hedge funds. For wealth management firms, we conduct case insensitive searches for terms such as "Wealth Manag", "Wealth MGNT", "Private", "PRVT" and "advisor". Hedge funds are identified through case insensitive searches for terms like "LLC", "L.L.C." "L L C", "L. L. C.", "LP", "L.P", "L P", "L. P", or "Partner". Fourth, we designate the remaining institutions as "Other" institutions and acquire their reported holdings. For all six types of institutions, we scale their quarterly lagged holdings by the total number of shares outstanding as the holdings and get: *Bank holdings*, *Hedge fund holdings*, *Insurance co. holdings*, *Mutual fund holdings*, *Other inst. holdings*, and *Wealth mgmt. holdings*. We then calculate the changes for each type of holdings from the previous quarter, treating these changes as trades from the respective institutions: *Bank trades*, *Hedge fund trades*, *Insurance co. trades*, *Mutual fund trades*, *Other inst. trades*, and *Wealth mgmt. trades*.

We adopt the methodology proposed by Barber et al. (2024) for computing retail trading.[19] First, we acquire daily off-exchange marketable orders from the *TAQ* trade dataset.

[19]The authors have modified the approach documented in Boehmer et al. (2021) for identifying and signing retail trades. They argue that retail orders that are internalized or executed by wholesalers often receive a

Specifically, we label a transaction as a retail buy if its execution price surpasses the quote midpoint, and classify it as a retail sell if the price falls below the quote midpoint. In the meantime, trades executed between 40% and 60% of the National Best Bid or Offer (NBBO) are excluded. Next, we aggregate intraday retail buy volume and retail sell volume for each stock on each trading day, calculating the order imbalance according to equation (A.1).

$$oib1_{i,t} = \frac{indbvol_{i,t} - indsvol_{i,t}}{indbvol_{i,t} + indsvol_{i,t}} \tag{A.1}$$

The remaining predicting variables consist of trades and lagged holdings from short sellers and firms. To begin with, we acquire quarter-end short interest data from *Compustat* and normalize it by the number of shares outstanding to derive the short interest ratio. Following the methodology outlined in McLean et al. (2022), we adjust the sign of the short interest ratio so that larger values signify fewer short positions. Next, we compute the change in signed short interest from the previous quarter to proxy for short seller trading. In this scheme, increases in the ratio indicate negative values of short seller trading, while decreases (reflecting a net closing of short positions) translate into positive values of short seller trading. As for firm trading, we subtract quarter-end share repurchases from share issues, scaled by the number of shares outstanding. Once again, we assign the sign of the variable such that decreases (or increases) in shares outstanding denote positive (or negative) values of firm trading.

A.2 Variable definition

LCP	The linear composite return predictor that is the monthly average of out-of-sample return premiums computed from six linear models, i.e., OLS, PCR, PLS, ALasso, Ridge, ENet.
NLCP	The nonlinear composite return predictor that is the monthly average of out-of-sample return premiums computed from six nonlinear models, i.e., ANN1, ANN2, ANN3, ANN4, GBRT, RF.
Bank holdings	Quarterly number of shares held by banks, scaled by the total number of shares outstanding.
Bank trades	Changes in bank holdings from the previous quarter.

small amount of price improvement relative to the quote midpoint, allowing for separating retail orders from institutional ones based on the sub-penny pricing of execution.

Hedge fund holdings	Quarterly number of shares held by hedge funds, scaled by the total number of shares outstanding.
Hedge fund trades	Changes in hedge fund holdings from the previous quarter.
Insurance co. holdings	Quarterly number of shares held by insurance companies, scaled by the total number of shares outstanding.
Insurance co. trades	Changes in insurance company holdings from the previous quarter.
Mutual fund holdings	Quarterly number of shares held by mutual funds, scaled by the total number of shares outstanding.
Mutual fund trades	Changes in mutual fund holdings from the previous quarter.
Wealth mgmt. holdings	Quarterly number of shares held by wealth management firms, scaled by the total number of shares outstanding.
Wealth mgmt. trades	Changes in wealth management holdings from the previous quarter.
Other inst. holdings	Quarterly number of shares held by remaining 13F institutions, after excluding mutual funds, hedge funds, banks, insurance companies, and wealth management firms, scaled by the total number of shares outstanding.
Other inst. trades	Changes in other 13F institutional holdings from the previous quarter.
Firm trades	Quarter-end share issues minus share repurchases, scaled by the number of shares outstanding. A negative sign is added to the variable, so a more negative (positive) value corresponds to more (less) firm trading.
Short seller holdings	Quarter-end short interest, scaled by the total number of shares outstanding. A negative sign is added to the variable, so larger values indicate fewer short positions.
Short seller trades	Changes in signed short interest from the previous quarter.
Size	The natural logarithm of firm market capitalization.
BM	Book-to-market ratio, calculated as the most recent fiscal year-end book value divided by the market capitalization.
MOM	Stock momentum, computed as the cumulative returns from month -12 to month -2.
STR	The short-term reversal, which is the prior month's return.
AG	Asset growth ratio, calculated as the annual asset growth from the previous fiscal year.
GP	Gross profitability, which is defined by dividing the gross profit by the total assets from the last fiscal year.
TO	Turnover ratio, which is the trading volume over the number

	of shares outstanding in the last month.
IVOL	Idiosyncratic volatility, which is computed as the standard deviation of the residuals from the Fama and French (1992) three-factor model of daily stock excess returns over the previous six months.

A.3 Machine-learning methods

We employ multiple machine-learning models to train the trades and holdings from nine market participants in order to obtain out-of-sample return premiums. We select the models that are adopted in recent academic papers (2019; 2020; 2023), given rapid advances in asset pricing studies using machine-learning techniques. The models can be categorized into either linear or nonlinear type.

We use the *sklearn* Python package to train the models. For models that requires tuning the hyper-parameters, we follow the literature by adopting the five-fold cross validation technique (Hastie et al., 2009). To briefly summarize, we divide the sample into five *folds* and then remove each *fold* in turn and evaluate the estimation errors associated with different sets of hyper-parameters. We choose the optimal hyper-parameter values that yield the minimum average estimation error.

Linear models

a) Ordinary least squares (OLS)

We start with a basic linear predictive regression model, ordinary least squares, where its wide adoption by research papers and its easy-to-interpret nature make it suitable for a benchmark model. The goal here is set to minimize the objective function that subjects to the parameter vector:

$$\min_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{N} (\alpha_{i,t+1} - \sum_{j=1}^{p} x_{ij,t} \beta_{ij,t})^2 \tag{A.2}$$

where a panel structure of training data regarding both T time points and N stocks are included in the function. Specifically, $\alpha_{i,t+1}$ is the excess return of the ith stock in month t + 1, $x_{ij,t}$ refers to one of the trades for the ith stock in month t, and $\beta_{ij,t}$ refers to the

parameter variable in the regression. Compared with machine-learning tools, a drawback of a multivariate OLS regression is the overfitting issue.

b) Ridge regression (Ridge)

One common way to improve the performance of multivariate linear regression is to employ a shrinkage method. The basic idea is to draw coefficient estimates closer to zero and thus avoid the scenarios when they become too large in magnitude (Gu et al., 2020). Ridge regression tends to improve the forecast accuracy by trading off a small increase in estimation bias for a large reduction in estimation variance. Specifically, ridge regression shrinks the regression coefficients through parameter penalization (Hastie et al., 2009), where the goal is to minimize a penalized residual sum of squares:

$$\min_{\beta}[\sum_{t=1}^{T}\sum_{i=1}^{N}(\alpha_{i,t+1}-\sum_{j=1}^{p}x_{ij,t}\beta_{ij,t})^2+\lambda\sum_{j=1}^{p}\beta_{ij,t}^2] \tag{A.3}$$

where the complexity parameter λ controls the magnitude of shrinkage and is set to be within [0.0001, 0.1]. Again, $\alpha_{i,t+1}$ is the excess return and $\beta_{ij,t}$ refer to one of the parameters. There are p trades for each stock i. The panel data cover T time points and N stocks in total.

c) Adaptive least absolute shrinkage and selection operator (ALasso)

Another common solution to alleviate the drawbacks of multivariate OLS regression in the machine-learning literature is employing least absolute shrinkage and selection operator (LASSO) in the predictor estimation (1996; 2019). In short, LASSO performs both shrinkage and variable selection, by minimizing the function as below:

$$\min_{\beta}\sum_{t=1}^{T}\sum_{i=1}^{N}[||\alpha_{i,t+1}-\sum_{j=1}^{p}x_{ij,t}\beta_{ij,t}||^2+\lambda\sum_{j=1}^{p}|\beta_{ij,t}|] \tag{A.4}$$

where λ is again the regularization parameter, with the ridge penalty $\sum_{j=1}^{p}\beta_{ij,t}^2$ in Formula A.3 replaced by the lasso penalty $\sum_{j=1}^{p}|\beta_{ij,t}|$ in Formula A.4.

Following Zou (2006), we adopt the adaptive LASSO method to further improves the estimation. Specifically, we assign different weights $w_{ij,t}$ to different parameters and λ again falls within [0.0001, 0.1]:

$$\min_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{N} [||\alpha_{i,t+1} - \sum_{j=1}^{p} x_{ij,t}\beta_{ij,t}||^2 + \lambda \sum_{j=1}^{p} w_{ij,t}|\beta_{ij,t}|] \tag{A.5}$$

where the weight is set to be $\frac{1}{|\hat{\beta}|}$. Each value of $\hat{\beta}$ is obtained from the first-step OLS regression residuals as follows:

$$\underset{\beta}{argmin} \sum_{i=1}^{N} (y_i - \sum_{j=1}^{p} x_{ij}\beta_j)^2 \tag{A.6}$$

d) Elastic net (ENet)

We also use Elastic net model that helps tune the training sample with the machine adaptively optimizes the hyper-parameters (Gu et al., 2020; DeMiguel et al., 2023). The general model incorporates both shrinkage and selection through the implementation of hyper-parameters, as follows:

$$\min_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{N} [(\alpha_{i,t+1} - \sum_{j=1}^{p} x_{ij,t}\beta_{ij,t})^2 + \lambda\rho \sum_{j=1}^{p} |\beta_{ij,t}| + \lambda(1-\rho) \sum_{j=1}^{p} \beta_{ij,t}^2] \tag{A.7}$$

where $\sum_{j=1}^{p} |\beta_{ij,t}|$ is the 1-norm and $\sum_{j=1}^{p} \beta_{ij,t}^2$ is the 2-norm of the parameter sets. Formula A.7 is a generalized representation built on Formula A.3 when $\rho = 0$ and Formula A.4 when $\rho = 1$. Any intermediate value of the hyper-parameter includes both types of regression. We set the hyper-parameter ρ to be 0.5 and λ within [0.0001,0.1].

e) Principal components regression (PCR)

Besides employing a penalty feature to solve overfitting issue in OLS, we alternatively adjust the baseline model with dimension reduction technique. By averaging across predictors, dimension reduction helps reduce noise and decorrelate among predictors, compared to simple OLS. Each trading signal p for stock i at time t $\sum_{j=1}^{p} x_{ij,t}$ in Formulas A.3 - A.7 can be further decomposed into k linear combinations of predictors as follows:

$$\sum_{j=1}^{p} \sum_{w=1}^{k} x_{ijw,t} W_{ijw,t} \tag{A.8}$$

which serves as a dimension-reduced version of the original predictor set.

We apply one of the dimension reduction tools, principal components regression (PCR), which involves a principal components analysis (PCA) that optimizes the covariance structure and then selecting some leading components in regression. Specifically, PCR chooses the combination weights $\sum_{w=1}^{k} W_{ijw,t}$ recursively, in order to find components that retain the most possible common variation within the predictor set. Although efficient in computation, PCR is unable to predict returns in the dimension reduction step, which leads to applying another method - partial least squares - that directly solves the drawback.

f) Partial least squares (PLS)

As another dimension reduction tool, Partial least squares (PLS) incorporates return prediction when exploiting covariance among predictors in the dimension reduction step (Gu et al., 2020). Unlike PCR, PLS estimates coefficients on return prediction for all univariate predictors and averages across predictors with the highest (lowest) weight on the strongest (weakest) predictors. By choosing components with more potent return predictability, PLS tends to let go the accuracy of weight matrix.

Nonlinear models

a) Gradient boosted regression trees (GBRT)

To take into account the nonlinear effect of predictors as well as their nonlinear interactions, we first adopt the regression trees model that brings multiway predictor interactions in a nonparametric way. To briefly explain, trees first identify and sort groups of observations with similar behavior and the sorting grows in a sequence. For observations in each group, simple averages of the outcome variable's values are taken to yield forecast. A simplified visualization is shown in Figure A.1, where we sort the observations based on characteristics size, weight, and color in sequence.

Although the trees model can capture interactions, it is subject to the overfitting issue. We tackle this problem by employing the gradient boosted regression trees model (GBRT) (Gu et al., 2020; DeMiguel et al., 2023), where the gradient boosting function combines decision trees in a sequence and it starts from weak decision trees and converges to strong trees. We set the hyper-parameter learning rate, which determines the weight given to the most recent decision tree, to be within 0.01, 0.1. In addition, we let the depth of the tree to fall within

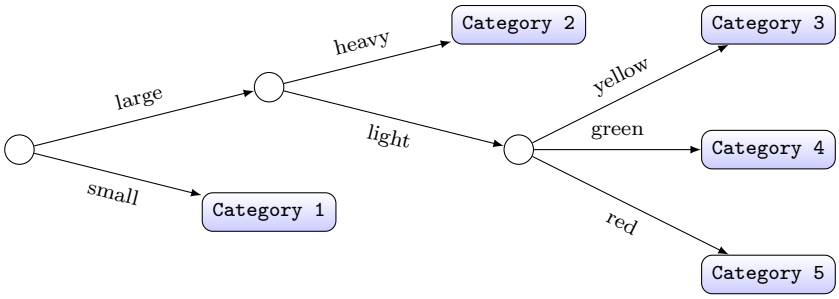


Figure A.1. Decision trees

1, 2, and the number of trees in out setting is within [1, 1000]. Overall, GBRT improves the forecasting performance by reducing the prediction variance as well as the prediction bias (Schapire and Freund, 2012).

b) Random forest (RF)

Similar to gradient boosting, a random forest (RF) method combines decision trees altogether. One key distinction between the two methods is that RF aggregates independent decision trees through bootstrap aggregation Breiman (2001) while GBRT aggregates the trees sequentially. Random forest method draws random subsets of the data, where for each sample it utilizes a distinct regression tree and then averages across the estimates to reduce the variance. It tends to reduce the correlation among predictions and thus the estimation variance. The number of trees is set to be 300, in accordance with Gu et al. (2020). We set the maximum depth in our setting to be between 1 - 6. The number of features in each split is within 1, 2, 3, 5, 10.

c) Artificial neural networks (ANN)

Lastly, we employ the artificial neural network model that entwines various telescoping layers of nonlinear predictor interactions. The model is regarded as a highly parameterized and complicated machine-learning tool. Specifically, we apply a commonly-used "feed-forward" network model (e.g., 2020; 2023), which includes *input layers* of predictors, *hidden layers* that capture complex interactions among the predictors, and an *output layer* for an outcome prediction through aggregating *hidden layers*. One illustration example of this "feed-forward" network is shown in Figure A.2.

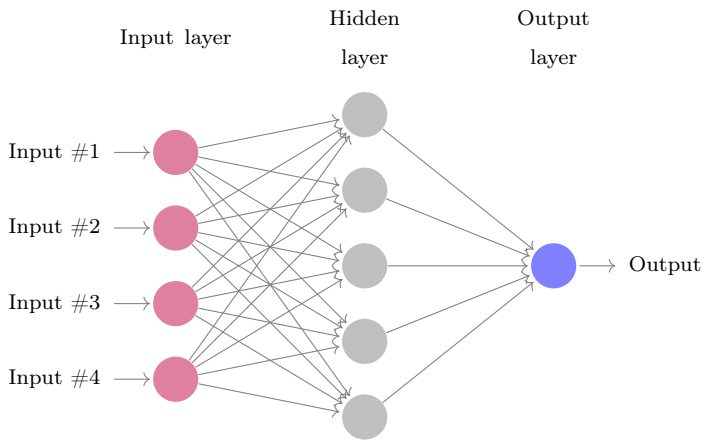


Figure A.2. Neural network

$$Tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{A.9}$$

$$ReLU(x) = \max(0, x) \tag{A.10}$$

We consider networks with up to four hidden layers (i.e., ANN1, ANN2, ANN3, ANN4). We follow Gu et al. (2020) for the setup of the hyper-parameters in the model, while we set the learning rate to be within 0.00001, 0.0001, 0.001.

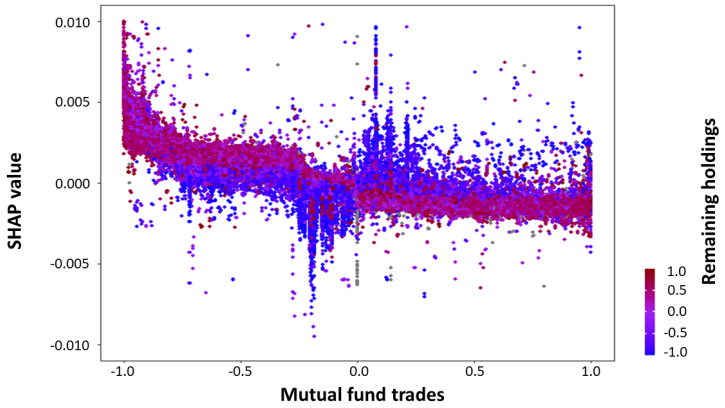
As for the nonlinear activation function, we choose two commonly-used functional forms: rectified linear unit (ReLU) and hyperbolic tangent (Tanh), and apply the activation functions at all nodes. To briefly explain, Tanh function in Formula A.9 helps transform the data into zero-centered data in order to make learning for the next layer much easier. ReLu function in Formula A.10 helps deactivate the nodes for which the output of the transformation is less than zero.

Appendix B Additional figures and tables

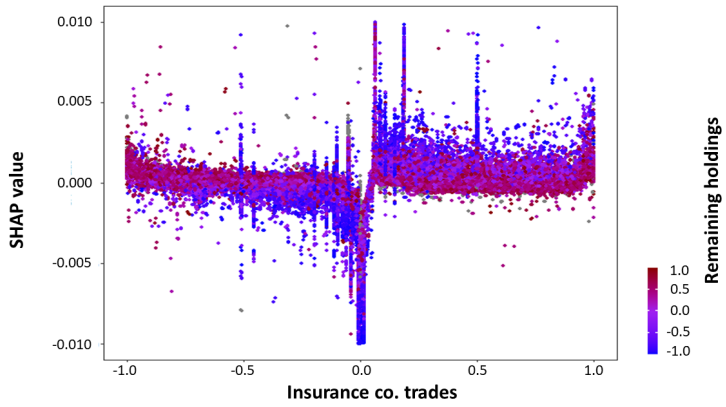
Figure B.1. Interactions between trading and holdings of remaining institutions

This figures illustrates the interactions between the trading of three types of institutions and the holdings of the remaining institutions. Panel A depicts the interaction between mutual fund trading and the aggregate holdings of institutional investors other than mutual funds, Panel B between insurance company trading and the holdings of the remaining institutions (other than insurance companies), and Panel C between wealth management firm trading and the holdings of the remaining institutions (other than wealth management firms). For each panel, the horizontal axis depicts the (standardized) trading variable and the vertical axis its SHAP value for each observation (dots). To visualize the interaction, we use color to display the original value of the holding of the remaining institutions (red for high value and blue for low value). We compute SHAP values for the last estimation window, which spans the period from December 2015 to November 2020.

Panel A. Mutual trading vs. remaining holding



Panel B. Insur. trading vs. remaining holding



Panel C. Wealth mgmt. trading vs. remaining holding

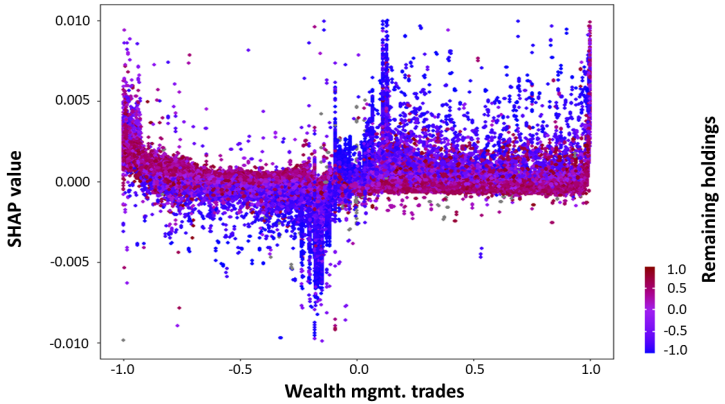


Table B.1. Alpha (q5+MOM) of univariate portfolios sorted by trades or lagged holdings

This table reports the alpha with respect to the Hou et al. (2021) and momentum factors of univariate portfolios obtained by sorting stocks based on the trades (or lagged holdings) of a single type of market participant. Panels A and B report the results for the univariate portfolios constructed using trades and lagged holdings, respectively. For each panel, the first column reports the name of the sorting variable, the second to seventh columns report the alpha of the low, second, third, eighth, ninth, and high decile portfolios, respectively, and the eighth column reports the alpha for the long-short portfolio, which goes long stocks in the high decile and short stocks in the low decile. At the end of each month, we rank all sample stocks based on either the trades or the lagged holdings of each market participant and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile as well as on the long-short portfolio and report their alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. To facilitate the comparison, we evaluate performance in the period from 2013 to 2020, which coincides with the out-of-sample period for the evaluation of the composite return predictors.

	L	2	3	8	9	H	**H - L**
Panel A: Trade sorts							
Banks	0.46%***	0.35%**	0.39%***	0.24%***	0.17%	-0.03%	-0.49%**
	(2.72)	(2.44)	(2.92)	(2.64)	(1.27)	(-0.29)	(-2.42)
Firms	0.24%	0.23%	0.63%***	0.37%*	0.36%***	0.19%	-0.04%
	(0.55)	(1.03)	(3.78)	(1.78)	(2.86)	(1.17)	(-0.09)
Hedge funds	0.22%*	0.18%	0.31%**	0.36%***	0.41%***	0.56%***	0.34%*
	(1.79)	(1.27)	(2.08)	(3.40)	(3.90)	(2.95)	(1.80)
Insurance co.	0.38%***	0.36%***	0.39%***	0.13%	0.06%	0.18%**	-0.19%
	(3.60)	(2.95)	(2.83)	(0.94)	(1.15)	(2.05)	(-1.31)
Mutual funds	0.62%***	0.43%***	0.46%***	0.13%	0.10%	0.23%***	-0.39%*
	(3.90)	(2.77)	(3.72)	(1.02)	(0.91)	(2.76)	(-1.89)
Other inst.	0.30%*	0.33%***	0.19%*	0.51%***	0.45%**	0.61%***	0.32%*
	(1.80)	(2.93)	(1.66)	(3.63)	(2.58)	(3.52)	(1.82)
Short sellers	-0.27%	0.18%	0.32%**	0.52%***	0.14%	-0.05%	0.22%
	(-1.18)	(0.98)	(2.17)	(4.62)	(0.87)	(-0.27)	(1.18)
Wealth mgmt.	0.59%***	0.46%***	0.58%***	0.32%***	0.22%*	0.15%	-0.44%***
	(4.36)	(4.34)	(3.74)	(2.80)	(1.87)	(0.96)	(-2.72)
Retail	0.39%**	0.45%***	0.27%**	0.03%	0.39%*	1.08%***	0.69%**
	(2.61)	(3.45)	(2.50)	(0.14)	(1.68)	(4.31)	(2.25)
Panel B: Lagged-holding sorts							
Banks	0.14%	0.87%**	0.97%***	0.03%	0.22%***	-0.03%	-0.17%
	(0.31)	(2.18)	(3.89)	(0.40)	(2.66)	(-0.37)	(-0.37)
Hedge funds	-0.03%	0.75%***	0.47%***	0.40%***	0.27%***	0.33%***	0.36%
	(-0.07)	(2.99)	(3.10)	(3.13)	(2.67)	(2.67)	(0.87)
Insurance co.	0.81%*	0.41%	0.84%***	0.06%	0.10%	0.06%	-0.74%*
	(1.89)	(1.01)	(2.76)	(0.70)	(1.53)	(0.66)	(-1.75)
Mutual funds	-0.28%	1.20%***	0.90%***	0.18%**	0.02%	0.04%	0.32%
	(-0.55)	(3.46)	(4.06)	(2.24)	(0.25)	(0.33)	(0.60)
Other inst.	0.00%	0.69%***	0.43%***	0.25%**	0.44%***	0.31%**	0.31%
	(0.00)	(3.10)	(2.88)	(2.60)	(4.08)	(2.05)	(0.70)
Short sellers	0.01%	-0.05%	-0.05%	0.41%***	0.69%***	1.53%***	1.52%***
	(0.03)	(-0.28)	(-0.39)	(4.46)	(3.26)	(4.89)	(4.70)
Wealth mgmt.	0.02%	0.68%*	0.69%***	0.19%*	0.31%***	0.34%***	0.32%
	(0.04)	(1.71)	(4.51)	(1.70)	(3.24)	(3.82)	(0.77)

Table B.2. Performance of individual machine-learning methods

This table reports the out-of-sample return and alpha of the long-short portfolios based on each of the twelve machine-learning methods. The first column reports the name of the machine-learning method, and the second, third, and fourth columns report the out-of-sample return, alpha with respect to the five Fama and French (2015) and momentum factors (FF5+MOM), and alpha with respect to the five Hou et al. (2021) and momentum factors (q5+MOM) of the long-short portfolio based on each of the 12 predictive methods: ordinary least squares (OLS), principal component regression (PCR), partial least squares (PLS), adaptive least absolute shrinkage and selection operator (ALasso), ridge regression (Ridge), elastic net (ENet), random forest (RF), gradient boosting regression trees (GBRT), and artificial neural networks with one to four hidden layers (ANN1, ANN2, ANN3, ANN4). At the end of each month, we rank all sample stocks based on one of the predictors, and then sort them into decile portfolios. We then compute the equal-weighted returns on the long-short portfolio and report the excess returns and alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	Return	FF5 + MOM	q5 + MOM
OLS	1.20%***	1.79%***	1.66%***
	(-3.52)	(-10.17)	(-6.23)
PCR	0.95%**	1.38%***	1.14%**
	(-2.38)	(-6.02)	(-2.54)
PLS	1.16%***	1.77%***	1.62%***
	(-3.54)	(-10.75)	(-7.01)
Ridge	1.21%***	1.60%***	1.67%***
	(-4.69)	(-12.36)	(-6.87)
Enet	1.15%***	1.56%***	1.61%***
	(-4.55)	(-9.91)	(-6.03)
Alasso	1.14%***	1.73%***	1.61%***
	(-3.33)	(-8.80)	(-5.96)
RF	2.03%***	2.29%***	2.18%***
	(-5.69)	(-5.62)	(-6.05)
GBRT	1.96%***	2.36%***	2.08%***
	(-8.14)	(-7.95)	(-5.83)
ANN1	1.59%***	1.97%***	1.69%***
	(-3.87)	(-7.49)	(-4.56)
ANN2	1.90%***	2.33%***	2.15%***
	(-5.43)	(-8.57)	(-6.25)
ANN3	1.88%***	2.19%***	1.98%***
	(-5.80)	(-7.46)	(-5.75)
ANN4	1.91%***	2.19%***	1.99%***
	(-5.85)	(-7.48)	(-5.81)

Table B.3. Performance of composite return predictors obtained excluding retail trades

This table reports the alpha of the portfolios of stocks sorted by the linear (LCP) and nonlinear (NLCP) composite return predictors obtained after excluding the retail trades from the input variables used to train the machine-learning methods. The first column reports the label for each decile portfolio and the long-short portfolio, the second and third columns report the alpha of each portfolio based on the LCP with respect to the five Fama and French (2015) and momentum factors (FF5+MOM) and the five Hou et al. (2021) and momentum factors (q5+MOM), the fourth and fifth columns for the portfolios based on the NLCP, and the sixth and seventh columns for the difference between the returns of the portfolios based on NLCP and LCP (NLCP minus LCP). At the end of each month, we rank all sample stocks based on either the LCP or NLCP, and then sort them into decile portfolios. We then compute the equal-weighted returns on each decile as well as on the long-short portfolio and report the alphas. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	LCP		NLCP		NLCP minus LCP	
	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM	FF5 + MOM	q5 + MOM
L	-1.04%***	-0.55%**	-1.35%***	-0.84%**	-0.31%	-0.30%
	(-3.74)	(-2.07)	(-3.86)	(-2.28)	(-1.58)	(-1.38)
2	-0.44%**	-0.10%	-0.39%**	0.00%	0.05%	0.10%
	(-2.49)	(-0.48)	(-2.29)	(0.01)	(0.34)	(0.63)
3	-0.18%	0.17%	0.17%	0.51%**	0.36%**	0.34%*
	(-1.05)	(0.89)	(1.01)	(2.57)	(2.10)	(1.95)
4	0.41%***	0.70%***	-0.01%	0.34%*	-0.41%***	-0.36%**
	(2.69)	(3.91)	(-0.05)	(1.84)	(-2.75)	(-2.08)
5	0.02%	0.38%**	0.07%	0.29%**	0.05%	-0.09%
	(0.18)	(2.29)	(0.58)	(2.22)	(0.33)	(-0.52)
6	0.23%*	0.38%***	-0.12%	0.10%	-0.35%**	-0.28%*
	(1.98)	(2.73)	(-1.35)	(1.06)	(-2.59)	(-1.91)
7	0.35%***	0.55%***	0.31%***	0.49%***	-0.04%	-0.06%
	(3.05)	(4.89)	(3.41)	(5.33)	(-0.32)	(-0.44)
8	0.52%***	0.78%***	0.51%***	0.72%***	-0.01%	-0.06%
	(3.84)	(4.93)	(3.05)	(4.20)	(-0.06)	(-0.35)
9	0.41%***	0.67%***	0.72%***	1.05%***	0.32%**	0.38%**
	(2.93)	(4.36)	(4.07)	(5.92)	(2.04)	(2.36)
H	0.72%***	1.14%***	1.08%***	1.46%***	0.35%	0.32%
	(3.66)	(5.16)	(4.17)	(4.83)	(1.65)	(1.14)
H-L	1.76%***	1.69%***	2.43%***	2.30%***	0.67%**	0.61%*
	(9.03)	(6.07)	(10.10)	(6.29)	(2.30)	(1.75)

Table B.4. Value-weighted portfolio performance and firm size

This table reports the alpha of the value-weighted portfolios of stocks sorted by the LCP (or NLCP) across sub-samples of stocks categorized by firm size. At the end of each month, we rank all sample stocks based on firm size and sort them into tercile portfolios. We then rank stocks within each tercile based on either the LCP or NLCP, and sort them into decile portfolios. We then compute the value-weighted returns on each decile as well as on the long-short portfolio and report the alphas with respect to the five Fama and French (2015) and momentum factors (FF5+MOM). The first column reports the label for each decile portfolio and the long-short portfolio, the second and third columns report the alphas for small firms, the fourth and fifth columns for medium firms, and the last two columns for large firms. The t-statistics are Newey-West adjusted and shown in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% level, respectively. The out-of-sample period for the evaluation of the composite return predictors spans from 2013 to 2020.

	Small		Medium		Large	
	LCP	NLCP	LCP	NLCP	LCP	NLCP
L	-2.04%***	-2.41%***	-0.41%*	-0.71%***	-0.27%	-0.13%
	(-4.39)	(-4.06)	(-1.76)	(-2.85)	(-1.64)	(-0.77)
2	-0.75%*	-1.11%**	-0.22%	-0.05%	0.13%	-0.23%
	(-1.95)	(-2.53)	(-1.24)	(-0.35)	(0.75)	(-1.09)
3	-0.11%	0.01%	-0.08%	0.29%*	0.31%*	0.08%
	(-0.31)	(0.02)	(-0.48)	(1.85)	(1.80)	(0.49)
4	0.34%	0.41%	-0.08%	0.09%	0.08%	0.07%
	(1.05)	(1.41)	(-0.61)	(0.71)	(0.61)	(0.62)
5	0.28%	0.04%	0.05%	-0.20%	-0.10%	0.10%
	(1.25)	(0.19)	(0.28)	(-1.49)	(-0.72)	(0.79)
6	0.82%***	0.57%***	0.12%	0.21%	-0.08%	0.19%
	(2.79)	(2.81)	(0.80)	(1.26)	(-0.85)	(1.65)
7	0.30%	0.37%	0.03%	-0.21%	-0.04%	-0.06%
	(1.30)	(1.25)	(0.16)	(-1.20)	(-0.30)	(-0.63)
8	0.59%**	0.59%***	0.27%*	0.05%	-0.14%	-0.10%
	(2.04)	(2.76)	(1.90)	(0.25)	(-0.80)	(-1.06)
9	0.55%*	1.22%***	0.02%	0.29%**	-0.19%	-0.07%
	(1.78)	(4.11)	(0.14)	(2.62)	(-1.63)	(-0.44)
H	0.96%***	0.89%***	0.28%	0.17%	0.40%***	0.23%
	(3.12)	(2.65)	(1.51)	(0.88)	(3.20)	(1.56)
H-L	3.00%***	3.30%***	0.69%**	0.87%***	0.67%***	0.36%
	(6.70)	(6.11)	(2.55)	(3.04)	(3.26)	(1.22)