Learning to Predict: Investor Experience and Bias in Signal Adoption

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Abstract

If learning from data were a purely statistical problem, investors endowed with an identical dataset would use it alike. They do not. In trading contests restricting investors to a common dataset, experienced participants respond more strongly to informative signals and enjoy higher performance, indicating a learning friction that erodes with experience. I also uncover a persistent familiarity bias toward recognizable signals. Mutual fund managers likewise tilt more strongly toward informative signals as experience accumulates. A model in which investor bias penalizes signal use unifies these findings; estimation reveals that bias declines with experience. In equilibrium, investors' biases sustain return predictability.

Keywords: Return Predictability, Familiarity Bias, Learning-by-Doing, Model Mis-Specification, Machine Learning
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1 Introduction

A large body of research has documented signals that predict stock returns.[1] Yet even professional investors appear to adopt these publicly available signals only weakly, if at all (Lewellen, 2011; Edelen, Ince, and Kadlec, 2016; McLean, Pontiff, and Reilly, 2025). Whether and how investors adopt valid signals determines whether return predictability persists, but little is known about this adoption process, or about why adoption is so limited. One possibility is that adoption frictions stem from investors themselves, not solely from the signals' predictive content.

If learning from data were a purely statistical problem, investors endowed with identical datasets would put them to identical use. This paper documents that they do not. In tightly controlled trading contests in which every participant is endowed with a common set of predictive signals, investors diverge widely in the performance they attain and in the signals their trading strategies act on. I interpret this divergence as the product of behavioral frictions in signal adoption. Part of the divergence is due to a learning friction that investors overcome by doing (Arrow, 1962): experienced investors respond more strongly to genuinely informative signals, the gains from predictability concentrate among them, and their actions partly converge. I also uncover a familiarity bias that favors adopting recognizable signals. Professional investors are likewise subject to a learning friction: I show that active mutual fund managers tilt their portfolios more strongly toward informative signals as they gain experience.

My main analyses exploit a tightly controlled prediction environment: a dozen trading contests run by the Quantiacs platform, which offers a standardized yet realistic setting that allows me to identify contestants' use of predictive signals. I examine 874 futures trading strategies submitted across these contests (launched during 2014–2019),[2] in which participants compete for profit-sharing contracts and are assessed on both in-sample and out-of-sample performance. Investors in this setting face a prediction problem (Martin and Nagel, 2022); namely, using the available signals on the Quantiacs platform to implement a trading strategy that translates signals into portfolio positions (which I do not observe). Critically, all contestants have access to identical sets of predictive variables – mostly, historical futures prices and, beginning in the eighth contest, 54 macroeconomic indicators – and cannot upload external data to the platform. The contests' design rules out a number of potential confounding factors, as I describe

[1] Cochrane (2011) argues for the importance of understanding this "factor zoo," and various replication studies collect and compare such signals that predict "anomaly returns" (e.g., Hou, Xue, and Zhang, 2020; Chen and Zimmermann, 2022; Jensen, Kelly, and Pedersen, 2023).

[2] Trading contest participants have access to machine learning and optimization tools, so any signal adoption frictions demonstrated by this group of subjects speaks to the use of machine learning tools by financial decision-makers more broadly (e.g., Sheng, Sun, Yang, and Zhang, forthcoming; Chen, Sialm, and Xu, 2025).

further in Section 2.1. As well as contest-level performance metrics, I also observe several decades' worth of daily portfolio returns and turnover, generated using a long sample of market data as input, from which I am able to infer signal usage. The divergence among investor outcomes is stark: within a contest, performance outcomes are widely dispersed, and the pairwise correlations of contestants' daily trading activity average no more than one-third.

Among investors who take part in the same contest, and are thus constrained to make use of an identical shared dataset, accumulated experience predicts better performance both in- and out-of-sample. I establish this result through panel regressions that include contest-level fixed effects, which uncover within-contest variation. Including additional investor fixed effects to control for unobserved, persistent heterogeneity such as skill further confirms that experience positively impacts both in-sample (backtest period) and out-of-sample Sharpe Ratios (SRs).

Within a contest the data are held fixed, so the experience gradient revealed by the panel regressions isolates differences in how investors use the same information. With experience, investors accumulate the ability to extract value from a given set of predictive signals, which they develop through a process of learning-by-doing. With the dataset held fixed, the primary margin along which such learning can operate is the selection and combination of the available signals into a trading strategy. I therefore hypothesize that inexperienced investors make sub-optimal use of these signals, and empirically examine this possibility.

To test this hypothesis, I compare how investors respond to signals of varying predictive power. To aid identification, I focus on their responses to a set of macroeconomic indicators made available in a later subset of trading contests. My test for sub-optimal signal usage requires two ingredients: a measure of how strongly an investor adopts given signals, and a measure of how informative those signals are. For the first, a trading contest participant implements her strategy as computer code that maps signals into positions, so signals that the code depends on move her positions on the days they update, while signals that it ignores do not pass through into position changes. The abnormal trading volume that coincides with a signal's update is therefore a measure of revealed signal adoption. For the second, I measure each macro signal's out-of-sample informativeness using Random Forest models (Gu, Kelly, and Xiu, 2020). Combining the two, I find that while all strategies adopt informative signals to some degree, those of experienced participants do so significantly more strongly.

Such differential signal adoption is consistent with learning-by-doing: experienced investors are better able to select and combine genuinely predictive signals. It also carries over to performance. Bringing signal informativeness into the performance regressions directly, I find that experience and informativeness interact: experienced investors earn incrementally higher

returns from the most informative signals. Comparing across information environments, before and after macro signals became available, the gains from the additional predictors likewise concentrate among experienced investors; the inexperienced do not benefit from them, on net.

Selection into continued participation does not explain the experience–performance gradient. Using a two-stage selection correction (Heckman, 1976), I find that the experience gradient remains positive after accounting for attrition. If anything, the estimated selection term suggests that uncorrected specifications *understate* the experience gradient, especially among investors with access to the additional macro predictors. Further tests indicate that the gradient is not an artefact of the contest environment: it cannot be explained by crash risk exposure, and is robust to changes in competitive intensity and to controlling for contestants' accumulated stocks of previously-developed strategies.

Additionally, I identify a familiarity bias in signal adoption, in which investors favor recognizable signals, consistent with availability-type heuristics (Tversky and Kahneman, 1973, 1974) or familiarity-based priors. I measure the familiarity of each macroeconomic indicator using past mentions in news and books; these text-based measures proxy for how recognizable a signal is to investors. Once more using trading strategy turnover on signal release days to reveal signal adoption, I find turnover is higher when the updated signals are more familiar, holding informativeness fixed: adoption responds to recognizability itself. The familiarity response is uniform across experience levels, rather than eroding with experience, suggesting the presence of a persistent bias. For inexperienced investors in particular, familiarity looms especially large relative to informativeness, to which they respond only weakly. The presence of a familiarity bias shows that signal adoption can depend on investors' subjective attitudes toward specific signals, beyond their objective statistical properties.

As investors learn to predict, their behavior also converges. Examining the cross-section of pairwise correlations in daily turnover, I find that experienced investors act more similarly to one another than inexperienced investors do, revealing a partial convergence in the predictive models that they implement. Convergence with experience indicates that the initial divergence among identically endowed investors reflects frictions that erode with learning, rather than stable heterogeneity in preferences or priors across investors. Since participants in a contest share a dataset, any dispersion in outcomes stems from different model specifications; convergence thus reveals a greater similarity in investors' models and trading strategies.

A model in which investor bias penalizes signal use unifies these findings. Extending Martin and Nagel (2022), I allow an investor solving a prediction problem to harbor a bias against incorporating valid signals. In closed form, the bias operates as a penalty on signal use, un-

der which she shrinks the weights on valid signals and may discard some entirely, behaving as a sparse decision-maker in the spirit of Gabaix (2014). Estimating the penalized prediction problem at the trading strategy level, I decompose the penalty into a signal-specific familiarity component and a general investor-specific subjective component. My estimates show that the investor-level component declines with experience. Learning is thus located within the investor: experience erodes her general bias against signal use, while allowing some signal-specific biases to persist.

The model also speaks to the persistence of return predictability. Embedding biased investors in a rational expectations equilibrium, I show that such biases can sustain return predictability even when every investor adopts the signal. Weak adoption of valid signals is thus not only a symptom of behavioral frictions but a channel through which predictability can endure in equilibrium.

I conclude my analyses by confirming that a learning friction operates beyond the trading contests setting. For this, I turn to an institutional setting where experience is observable: the common stock portfolios of actively managed mutual funds. I measure signal adoption using quarterly portfolio holdings, building on a literature that infers characteristic tilts and portfolio preferences from disclosed positions;[3] specifically, based on 208 firm-level predictors collected by Chen and Zimmermann (2022), I construct portfolio–signal–quarter tilts that capture whether a fund manager overweights stocks that a given signal ranks as having higher expected returns (net of the market's exposure). I find that more experienced managers tilt more strongly toward informative signals. The gradient survives manager fixed effects and manager $\times$ portfolio fixed effects that absorb manager–fund matching, and it emerges despite strong institutional frictions (such as mandates) that could easily swamp individual-level learning. Together with the contest evidence, this finding indicates that the behavioral learning friction in signal adoption is a robust feature of investor behavior across domains.

Related Literature. This paper contributes to a growing literature emphasizing that the value of predictive information depends not only on statistical accuracy but also on how agents convert signals into decisions (Kleinberg, Ludwig, Mullainathan, and Obermeyer, 2015).[4] I present novel empirical evidence on investors' adoption of predictive signals, including in a

[3] See, among others, Grinblatt, Titman, and Wermers (1995), Del Guercio (1996), Bennett, Sias, and Starks (2003), Lewellen (2011), and Lettau, Ludvigson, and Manoel (2018). Portfolio holdings are revealing because investors must hold the stocks implied by predictive signals to earn the associated next-period anomaly returns.

[4] In non-prediction-related settings, well-known inefficiencies in the use of information include distraction and limited attention (e.g., DellaVigna and Pollet, 2009), imperfect understanding (Cohen and Frazzini, 2008), a failure to notice features of the environment (Hanna, Mullainathan, and Schwartzstein, 2014), theoretical models of sparse attention and selective information processing (Matějka and McKay, 2015), and more general processing costs (Blankespoor, deHaan, and Marinovic, 2020).

setting where subjects implement predictive models in the form of computer-coded trading strategies and can employ machine learning tools and optimization routines. The central role of experience gradients in predictive signal adoption (and its link to investor performance) adds a new dimension to our understanding of how investors learn from experience (e.g., List, 2003; Nicolosi, Peng, and Zhu, 2009; Choi, Laibson, Madrian, and Metrick, 2009; Greenwood and Nagel, 2009; Seru, Shumway, and Stoffman, 2010). My findings establish learning-by-doing (Arrow, 1962) as a driver of predictive signal adoption: among investors endowed with identical data, experience governs which signals are adopted. I also document a familiarity response in signal adoption, extending the reach of familiarity effects beyond stock selection (Huberman, 2001; Seasholes and Zhu, 2010). Furthermore, I microfound a penalized prediction problem in which behavioral bias acts as a penalty on signal use, connecting biased signal adoption to sparsity-based models of limited attention (Gabaix, 2014; Bastianello, Décaire, and Guenzel, 2024), with a generalization to signal-specific penalties to allow for more general biases. My results also shed light on the drivers of model disagreement (Cookson and Niessner, 2020; Montiel Olea, Ortoleva, Pai, and Prat, 2022).

As well as contributing to understanding prediction and adoption behavior in general, this paper speaks directly to a literature on how investors behave in the presence of *return* predictability. Lewellen (2011), Edelen, Ince, and Kadlec (2016), and McLean, Pontiff, and Reilly (2025) argue that institutional investors fail to exploit return predictability; I provide direct evidence on how investors adopt such signals. Chen, Hwang, and Peng (2025) study the rationales that certain market participants offer when recommending stocks whose characteristics tend to predict low excess returns; in contrast, I examine investors' systematic trades and portfolio tilts across a broad set of predictive signals, linking them to both investor and signal characteristics. Andries, Bianchi, Huynh, and Pouget (2025) run a laboratory experiment in which subjects are endowed with a single predictive signal and study how it influences subjects' own return forecasts; I examine a realistic setting in which investors must select and combine signals from a high-dimensional set to form a trading strategy (i.e., specify a model). My analysis is also distinct in uncovering the roles of learning-by-doing and familiarity as mechanisms that shape how investors respond to return predictability.

These behavioral frictions also speak to a broader debate in asset pricing over why return predictability can persist after signals become public, a question that encompasses debates over whether documented predictors reflect data mining versus genuine regularities (Harvey, Liu, and Zhu, 2016; Linnainmaa and Roberts, 2018; Hou, Xue, and Zhang, 2020; Chen and Zimmermann, 2022; Jensen, Kelly, and Pedersen, 2023), and to whether anomaly returns reflect mispricing versus compensation for risk (Fama, 1998; Barberis and Thaler, 2003). Focusing on

a comprehensive set of published and replicated predictive signals (Chen and Zimmermann, 2022), I document a number of novel behavioral frictions – a learning friction overcome by doing, and a familiarity bias – that limit adoption even when predictors remain informative. Martin and Nagel (2022) show that market efficiency depends on how agents process high-dimensional data; therefore, the frictions I uncover are a potential source of mispricing.

My paper also relates to multiple strands of the mutual funds literature; first, on fund managers' use of public information as a skill (Kacperczyk and Seru, 2007; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016), and on whether data and labor are complements or substitutes (Abis and Veldkamp, 2024; Bonelli and Foucault, 2023). Second, on examining funds' portfolio tilts (Lewellen, 2011) or trading activities (Edelen, Ince, and Kadlec, 2016; McLean, Pontiff, and Reilly, 2025) to quantify the extent to which they exploit return anomalies. And third, on the role of accumulated experience as a driver of skill (Cici, Gehde-Trapp, Göricke, and Kempf, 2018; Kempf, Manconi, and Spalt, 2017). My evidence builds on these studies by showing that the adoption of predictive signals is a specific dimension of manager skill, and one that improves with experience. I also identify behavioral mechanisms through which this occurs (as opposed to institutional and organizational constraints) by analyzing controlled trading contests in addition to mutual fund portfolios.

I describe the trading contests setting further in Section 2. Section 3 documents an experience gradient in performance. Section 4 uncovers the adoption of informative and familiar signals. Section 5 shows the gains from predictability concentrate among experienced investors, and rules out non-learning based explanations for the experience gradient. Section 6 formulates, tests, and generalizes a model of biased investors solving a prediction problem. Section 7 provides evidence from the portfolios of active mutual fund managers. Section 8 concludes. The Appendix contains tables and figures. An Internet Appendix contains all proofs, together with additional analyses and descriptions.

2 Trading Contests: Institutional Setting and Data

I now describe the controlled trading contest setting, the observable outcomes, and the institutional features that allow me to study predictive signal adoption while holding fixed investors' information sets and incentives.

2.1 The Quantiacs Trading Platform and Trading Contests

Quantiacs is a FinTech platform that runs simulated trading contests for investors who design systematic trading strategies. The business model of Quantiacs is to identify the best 3 contestants in each contest and allocate assets to them, thus building up a portfolio of multiple delegated systematic trading strategies.[5]

Contestants upload code (in Python or Matlab) to implement a strategy that takes long or short positions in futures contracts, and each strategy's performance is assessed based on its in-sample ("backtest") Sharpe Ratio prior to the start of the contest, and its out-of-sample ("live") Sharpe Ratio during the contest period. The official scores assigned to entries incorporate the out-of-sample Sharpe Ratio, and so this incentivizes traders to perform well out-of-sample.[6] In-sample performance is determined from historical daily data, and this is visible to traders as they backtest and fine-tune their strategy ahead of a contest launch. The Sharpe Ratios reported by the trading platform include the effect of simulated transaction costs, which the investors also perceive. Out-of-sample performance is calculated using market data that arrives after the launch of a contest; i.e. during the Live period. During this Live period, contestants are unable to modify their trading strategy in any way whatsoever. Each trading strategy updates portfolio positions at a daily frequency. The Live period of each contest lasts for approximately 3 months, and the 12 contests in my panel thus cover a number of years in out-of-sample/live calendar time. Figure 1 illustrates the distinction between the in-sample/backtest and out-of-sample live periods of a contest.

[Insert Figure 1 here]

To make the institutional setting more concrete, Internet Appendix C presents screenshots of the Quantiacs platform that illustrate the steps taken by an investor to code up, backtest and then submit a trading strategy entry to a contest.

The Quantiacs setting is realistic in a number of ways that are difficult to achieve in a laboratory. First, the platform uses actual market data throughout; experimental studies tend to rely on simulations of simplified data-generating processes. Second, investors are granted access to a sophisticated backtesting facility and software packages, and have weeks to design

[5] Case studies by Fleiss, Kominers, and Ughetta (2017) and Zheng (2017) describe the business model further. I emphasize that my sample is limited to entries to the open-entry trading contests in which investors are on an equal footing, and does not include any observations from profit-sharing trades.

[6] An entry's official score is defined to be the minimum of its in- and out-of-sample Sharpe Ratios. Since in-sample Sharpe Ratios are known at the end of the Backtest period, the investor's problem at the beginning of the Live period is indeed to maximize the out-of-sample Sharpe Ratio. In Internet Appendix G.4, I check that results are robust to using the official score instead of the out-of-sample SR.

and refine their trading strategies. Most importantly, participants are offered significant financial incentives: investors are incentivized by the offer of profit-sharing contracts of 10% of net profits on an allocation of $1 million, $750,000 & $500,000 to the 3 best-performing investors in each contest, respectively. These features make the contest setting closer to a real prediction environment than a standard laboratory task.

At the same time, the trading contests setting constrains participants in ways that ensure empirical comparisons between them are fair. First, the human investors are required to implement trading strategies in the form of computer code that runs remotely on the Quantiacs platform, and which they cannot modify during a contest. Beyond submitting the code, contestants do not review or approve the portfolio updates generated by their strategies; thus their predictive model remains fixed. Second, the contest setting assigns all investors a common, well-defined goal (incentivizing them to maximize their trading strategies' out-of-sample Sharpe Ratios) and endows them with a common dataset of predictive variables for use as inputs to their systematic trading strategies; investors cannot upload their own datasets. Furthermore, the contest setting fixes investors' preferences (due to the common goal), horizons (contest period) and other well-known drivers of portfolio choice that might confound my analysis.[7]

Entry to one or more contests is free upon registration. Contest live periods are non-overlapping. I am able to observe individual investors' performance outcomes at an individual trading strategy level. For confidentiality reasons, I am unable to observe the granular positions taken by trading strategies, or the code used to implement them. The platform did not collect identifying information from contestants, and did not require them to provide any demographic characteristics.

While investors share a common and fixed information set *within* a contest, the Quantiacs platform widened the set of available variables in between contests: macroeconomic indicators were added to investors' historical and live trading datasets after the end of the 7th contest and before the beginning of the 8th contest. Out of a total of 12 contests, investors in the first 7 therefore had narrower datasets than investors in the final 5. I exploit this variation in the (common) information set across contests to test whether the gains from newly available predictive signals are uniform or instead concentrate among investors with enough experience

[7] In addition to the commonly-enforced objective, investors are in a perfectly competitive setup because they cannot affect each others' payoffs through price impact or observability of actions, thus freeing them from the usual strategic considerations. Background risk or other wealth effects do not enter into investors' objectives, either, since no payment or stake is required to enter into a contest. Investors are fully committed to following their trading strategies during the out-of-sample phase of each contest, as it is no longer possible to modify a contest entry's computer code at that stage.

to incorporate them into their predictive models. Sections 2.2.3 and 2.3 provide further details, and additionally describe the (irregular) release schedules of different macroeconomic indicators.

2.2 Data from Trading Contests

2.2.1 Contest Leaderboard Panel

My leaderboard sample consists of 874 trading strategies entered into 12 trading contests spanning a number of years. I can identify individual traders who may (and often do) take part in multiple contests over time in order to measure performance dynamics. I can also exploit the panel structure of the leaderboard dataset to incorporate fixed effects in my regressions to conduct within-investor analyses.

[Insert Table 1 here]

Table 1 summarizes this leaderboard panel, including investors' in-sample and out-of-sample performance. When entering a trading strategy into a contest, most investors will have implemented a strategy that has performed well over the recent backtest period: the contest-level median in-sample Sharpe Ratio (SR) ranges from +0.38 to +1.19 units of SR. Most investors therefore *appear* to benefit (in the sense of enjoying a positive SR) when their performance is assessed on past market data alone.

However, their performance degenerates out-of-sample; i.e., in contest Live periods, during which trading strategies can no longer be modified by investors. In those periods, the contest-level median SR ranges from only -1.21 to +1.00 units of SR. Furthermore, the median is positive for only a third of all contests, suggesting that most investors typically do *not* enjoy a positive SR benefit. Better-performing investors can benefit considerably: the top quartile of performance in contest Live periods is typically positive, and this upper quartile level can range as high as 2.07 units of SR. Similarly, the top decile performers in each contest Live period always succeed in attaining a positive SR out-of-sample; in ten of the contests, these top performers consistently exceed 1.4 units of SR.

Comparing investors over the same periods reveals that the dispersion in investor performance is substantial. For the out-of-sample SRs obtained during contest Live periods, the interquartile range for these is typically 2 to 3 units of SR. That is, the 75th-percentile investor typically obtains a SR that exceeds the 25th percentile investor's by over 2 units during the same contest Live period. Sharpe Ratios vary over time, being (scaled) returns, and yet this dispersion persists over much of the 2014-2019 period, in which contest Live periods run.

Contestants are able to enter multiple trading strategies into the same contest, yet the median contestant submits just one entry. In subsequent analyses, whenever a contestant submits multiple entries I include only the best-performing entry; hence, panel regressions contain a single entry per contestant–contest. In reviewing the raw data, I identify as outliers two contestants who submitted an extremely high number of entries (over 100) to a contest, and so exclude these two contestants from any analyses in this paper. Internet Appendix D contains additional details on the frequency of participation.

2.2.2 Timeseries of Daily Returns and Volume for Trading Strategies

I supplement the comprehensive contest leaderboard panel with two additional datasets. Quantiacs separately makes available the daily returns of trading strategies, which I merge with the leaderboard panel. And, while granular portfolio positions remain confidential and thus unobservable, I can observe two daily positioning indices per trading strategy: the aggregate long positioning $Long_{i,\tau}$ and the aggregate short positioning $Short_{i,\tau}$. These are computed by the platform based on portfolio weights $w_{i,j,\tau}$ as $|Long_{i,\tau}| + |Short_{i,\tau}| = \sum_j |w_{i,j,\tau}|$. I use these indices to measure a strategy i's trading volume on calendar day τ as

$$Volume_{i,\tau} = \left|Long_{i,\tau} - Long_{i,\tau-1}\right| + \left|Short_{i,\tau} - Short_{i,\tau-1}\right|. \tag{1}$$

Figure 4 shows that trading activity is heterogeneous, much like the performance outcomes examined previously. I compute the pairwise correlation between the daily aggregate turnover series of a contestant's trading strategy in each contest and the equivalent turnover series for every other contestant in the same contest, excluding self-comparisons: I label this $\rho_{i,j,t}$ for trading strategies i, j in the same contest t. The figure displays the contest-level means of these pairwise correlations in trading activity. The yardstick of perfect agreement would correspond to a mean pairwise correlation of +1 in each contest; instead, the levels never exceed 0.4. This alternative characterization of disagreement based on trading activity also suggests that investors disagree strongly.

[Insert Figure 4 here]

The observed within-contest dispersion in performance has an important implication: trading strategies with access to precisely the same dataset still vary widely in their attained performance. When conditioning on any one contest index, investors have access to exactly the same set of predictive variables and their historical realizations; therefore, conditioning on the contest also conditions on investors' information sets. Since investors in the same contest are symmetrically informed, within-contest dispersion is likely to reflect differences in how

investors interpret, select, and combine the same data. Cookson and Niessner (2020) term this phenomenon "model disagreement," to distinguish it from disagreement that is due to heterogeneous information.

2.2.3 Macroeconomic Signals and Their Release Dates on the Trading Platform

The additional set of predictive signals added to the platform in between contests consists solely of macroeconomic indicators. Internet Appendix F provides a full listing.

I use the exact values of these macroeconomic signals as they were accessible to investors' trading strategies when running on the Quantiacs platform. I am also able to identify precisely the date on which each macroeconomic variable was updated on the platform (for both backtesting & live trading periods); I can therefore identify exactly which trading date return is the first to incorporate an updated macro signal.

[Insert Figure 2 here]

Figure 2 is a stylized illustration of the two dimensions of time (t, τ) in the Quantiacs institutional setting. Investors enter a trading contest, indexed by t. Macro indicators were only accessible on the trading platform to investors and their trading strategies from contest $t \geq 8$ onward. The trading platform inputs each trading strategy (implemented in code) at a daily frequency with a set of daily predictive signals extending back to January 1990, and each code execution returns a set of daily portfolio weights; this vector of portfolio weights is the output of each trading strategy. The daily-frequency trading strategy calendar time is indexed by τ, and comprises both the backtest/in-sample and live/out-of-sample calendar periods. I later use the exact macroeconomic signal release dates (occurring on some days τ) to analyze the responses of contestants' trading strategies to input signals.

2.3 Institutional Variation in Macro Release Day Informativeness

When the Quantiacs platform updates the values of the macroeconomic variables that are available as inputs to trading strategy code, it does so on a single calendar date per month; thus, these release dates do not necessarily correspond to macro variable announcements by statistical agencies. Not all variables are updated every month, and this is particularly true for early periods in the backtest history, when a number of variables were not backfilled. Figure 3 illustrates the variation in the number of macroeconomic signals that are released by the Quantiacs platform to trading strategies running on the platform, in trading strategy calendar time τ.

[Insert Figure 3 here]

I later exploit this institutional variation in the timing of macro signal releases to measure trading strategy responses to different types of signals.

3 Evidence of Learning Frictions

Section 2.2 established that identically endowed investors diverge widely in performance and in trading activity. This section documents a systematic pattern in this divergence. I uncover an experience gradient in performance that holds within contests, where the data are identical across investors, and then show that experienced investors' revealed trading rules partly converge. Together, these results suggest investors are subject to learning frictions that erode with experience.

3.1 Performance Outcomes and Experience

I begin by testing whether experience drives improved performance. I measure two types of performance outcome: the in-sample (backtest period) Sharpe Ratios and the out-of-sample (live period) Sharpe Ratios of the contestants i for each contest period t. An investor's experience is measured by the number of contests she has participated in so far. I conduct regressions that are variants of the specification

$$\text{SR}_{i,t} = \beta \times \text{Contests Experienced}_{i,t} + \pi_i + \phi_t + \epsilon_{i,t}, \tag{2}$$

where π_i denotes investor (contestant) fixed effects and ϕ_t denotes time (contest) fixed effects. Controlling for these two dimensions of unobserved heterogeneity allows me to exclude their effect on observable performance outcomes; for example, unobserved investor-specific attributes (including demographic characteristics or skill levels) are taken into account.

[Insert Table 2 here]

Table 2 displays the results of regressing performance outcomes against the experience levels of the contestants. In both OLS and panel specifications, the positive (and significantly non-zero) coefficient β on investor experience indicates investors perform better as they accumulate experience. Importantly, the inclusion of contest fixed effects ϕ_t in specifications (2) and (5) conditions on a common dataset, in both the set of signals available and the number of historical observations; all contestants within a contest face an identical dataset. The experience gradient therefore reflects differences in how investors use the data they are given. The positive and significant coefficients shown in (2) and (5) thus reveal that more experienced

investors attain a better performance outcome conditional on identical datasets, consistent with learning-by-doing. Furthermore, the inclusion of individual fixed effects π_i in specifications (3) and (6) controls for any contestant characteristics that do not vary across contests, including unobserved ones such as innate ability, prior experience with financial markets, or sociodemographic characteristics. The positive gradient between experience and performance is also observed for both in-sample (columns 1–3) and out-of-sample (columns 4–6) performance outcomes.

3.2 Model Disagreement and Experience

I now test whether model disagreement lessens with experience, concurrently with the improvement in investors' performance. For this, I rely on the pairwise correlations between the aggregate daily turnovers of trading strategies i, j matched to the same trading contest t (the means of which were shown in Figure 4). I perform an additional matching/filtering step: I retain only individual pairwise correlations $\rho_{i,j,t}$ for which contestants i and j have the same level of experience. I then conduct variants of the following panel regression:

$$\rho_{i,j,t} = \beta \times \text{Contests Experienced}_{i,j,t} + \pi_i + \phi_t + \epsilon_{i,j,t}. \tag{3}$$

This procedure relates the average pairwise correlation between entries (left-hand side) to the matched experience levels of the contestants who implemented the trading strategies (right-hand side). The fixed effects allow me to progressively control for two of the three dimensions along which the panel varies: the contest index t and one of the contestant indices i.

[Insert Table 3 here]

Table 3 displays the regression results. The simplest specification in column (1) produces an easily-interpretable measure of the mean pairwise correlation between the daily trading volumes of all participants with the same experience level. This proxy for model agreement ranges from 0.3 to 0.4.

Across all specifications 1–3, an increase in the number of contests experienced by (both) contestants i and j is associated with an increase in the correlations of their trading strategies' daily turnover, of around 6 to 9 percentage points. Experience is therefore associated with less model disagreement, consistent with experienced investors converging toward more similar revealed trading rules. Convergence with experience also sharpens the interpretation of the within-contest divergence documented in Section 2.2: dispersion that erodes as investors accumulate experience reflects frictions in how they specify predictive models, rather than stable heterogeneity in preferences or priors.

4 Signal Adoption in Trading Contests

The previous section established that experienced investors outperform novices even conditional on identical datasets, consistent with learning-by-doing. A natural mechanism is that experienced investors make better use of the predictive signals on the platform. I test this hypothesis by measuring how investors' trading strategies respond to variation in the information content of macro release days on the Quantiacs platform.

4.1 Measuring Macro Signal Informativeness

To construct a measure of the predictive information content of different macro release days τ, I use a methodology from the literature on interpretable machine learning that allows individual variable informativeness to be measured and then aggregated to groups of variables.

Benchmark Predictive Model. I begin by defining a benchmark machine learning model to detect out-of-sample return predictability. I use the Random Forest algorithm (Breiman, 2001) as my estimation technology; this algorithm has proven successful in detecting out-of-sample equity return predictability (Gu, Kelly, and Xiu, 2020), and is therefore a suitable benchmark to compare human behavior to. As this empirical literature shows, a Random Forest can capture flexible and nonlinear predictive relationships, and is capable of incorporating the full set of high-dimensional macroeconomic predictive variables in my setting. I set up the following cross-sectional return prediction problem, where i indexes a futures contract and τ a month:

$$r_{i,\tau+1} = \mathbb{E}_t[r_{i,\tau+1}] + \epsilon_{i,\tau+1}, \tag{4}$$

with the conditional prediction for each next-month return

$$\mathbb{E}_\tau[r_{i,\tau+1}] = f(\boldsymbol{x}_\tau) \tag{5}$$

given by a flexible nonparametric mapping f estimated by the Random Forest algorithm, and which uses a vector $\boldsymbol{x}_\tau$ of predictive variables available as of the end of month τ.

I define the predictive variables $\boldsymbol{x}_\tau$ as the last 3 lags (on a monthly basis) of all 54 macroeconomic predictive variables available on the Quantiacs platform. Missing values are imputed with the historical median and each series is standardized to have zero mean and unit standard deviation. Both imputation and standardization only use data up to 2013 to avoid introducing any look-ahead bias to the OOS (out-of-sample) predictions that are generated for 2014 onwards (the period in which Quantiacs contest Live periods fall). In addition, one dummy

variable for each futures contract is included in the set of input variables $\boldsymbol{x}_\tau$. This is somewhat analogous to including fixed effects in a regression but allows much more flexibility: including these indicators allows an estimated Random Forest to nest up to one predictive sub-model per futures contract if necessary.

As I will be making implicit comparisons between the performance of contestants' systematic trading strategies and my benchmark algorithm, the comparison is constructed to be fair. First, the benchmark machine learning algorithm that I construct uses only data $\boldsymbol{x}_\tau$ that is accessible on the Quantiacs platform to contestants. Second, the Random Forest algorithm is a popular and well-known technique, with Breiman's (2001) paper having received over 6,000 citations on Google Scholar by the time macro signals are added to the Quantiacs platform.[8] Third, I use a software package that was available to Quantiacs participants to conduct my estimation (`scikit-learn` (Pedregosa et al., 2011)) and which includes a pre-packaged implementation of a Random Forest algorithm. Finally, I take care to avoid look-ahead bias, as I describe shortly. Thus, given the dataset, software and prediction technology that I use, the Quantiacs participants could have performed a similar analysis to what follows.

My Random Forest estimation and tuning procedure is similar to that of Gu, Kelly, and Xiu (2020). I estimate predictive models at an annual frequency: for example, to predict futures returns for any month in 2014, I use a model that has been trained up to the end of 2013. The training procedure involves using a validation set for the 5 year period preceding the test set – for example, to produce 2014 forecasts, the validation set would run from 2009 to 2013. Multiple models are estimated for various sets of hyperparameters,[9] and evaluated on the validation set. After picking the optimal set of hyperparameters, the model is then re-estimated for the period 1990 up to the year before the test set – for example, to produce 2014 forecasts, the model has been estimated from 1990 to 2013. This ensures that the test set forecasts (for example, 2014) are true OOS predictions. For the next year of the test set (for example, 2015), the entire procedure is repeated with an expanded training set and a validation set that has rolled forward by one year.

In this manner, monthly OOS predictions are generated for the period 2014–2019. The Quantiacs platform prevents models from improperly using OOS data in order to avoid look-ahead bias. This careful procedure is therefore necessary to accurately capture genuine OOS predictability, which a Quantiacs contestant must try to exploit in order to achieve her objective

[8]Furthermore, the Random Forest also regularly appears in introductory articles and books on applied machine learning: as one example out of many, an article on Coursera titled *"7 Machine Learning Algorithms to Know: A Beginner's Guide"* introduces the Random Forest algorithm.

[9]Refer to Gu, Kelly, and Xiu (2020, Internet Appendix Table A.7) for further details.

of maximizing her OOS Sharpe Ratio.

My procedure for constructing a benchmark predictive model that uses all the macroeconomic signals available on the Quantiacs platform successfully estimates a model that detects out-of-sample return predictability. As one example of how this predictability can translate into portfolio choice, I cross-sectionally rank predicted returns and form a monthly-rebalanced portfolio that goes long futures contracts in the highest quintile of predicted next-month returns and short the lowest quintile of predicted next-month returns, with equal weightings to futures contracts. This example strategy earns a cumulative OOS return of 40.91% and an OOS Sharpe Ratio of 0.57 over the period (assuming a zero riskless rate for simplicity).[10] Note, however, that specifying a trading strategy is not necessary for my measure of informativeness; rather, these results are illustrative.

Informativeness of Individual Macro Signals. To measure the informativeness of individual variables in the predictive model input $\boldsymbol{x}_\tau$ I use SHAP values (Shapley Additive Explanations) (Lundberg and Lee, 2017), which possess the useful property of additivity. Define $SHAP(k,m)$ as the SHAP value of individual predictive variable k for data sample m; a sample consists of the futures contract and prediction month. The SHAP value of a variable k measures the predictive power of variable k for the individual prediction indexed by m. Like the prediction, the SHAP value is in units of return. Note that the SHAP value depends on the estimated model used, and models are matched to the contest taken part in, making sure to avoid any look-ahead bias.

Informativeness of Macro Signal Release Days. The additivity of SHAP values allows me to easily aggregate them up to a daily index. Recall that each macro release day τ is associated with a set of simultaneously-released variables $\mathcal{R}(\tau)$ (and a complementary set of variables that are *not* updated during that macro release day). Thanks to the additivity of SHAP values, a single SHAP value per macro release day τ and data sample m can be computed by summing up the SHAP values of the variables released that day:

$$SHAP(\tau,m) = \sum_{k\in\mathcal{R}(\tau)} SHAP(k,m). \tag{6}$$

[10] It is possible that these results serve as a lower bound to the extent of macroeconomic signal-based predictability, since the input variables consisted solely of the (lags of) the levels of these variables, and so constructing further variables out of these may increase the level of measured OOS predictability. Similarly, more sophisticated machine learning methods could be employed for the task of measuring the extent of return predictability using these variables. It is not the goal of this study to examine OOS predictability among futures contracts, but my findings suggest such a study could be informative.

I then compute an informativeness index for each macro release day τ as the mean absolute SHAP value across all M data samples:

$$\text{Informativeness}_\tau = \frac{1}{M}\sum_m \left|SHAP(\tau, m)\right|. \tag{7}$$

Eqn. (7) measures the extent to which the set of variables $\mathcal{R}(\tau)$ released on a macro release day τ have predictive power across the entire cross-section of futures contracts, irrespective of sign, and for all historical dates.

Validating that Trading Strategies Respond to Updated Macro Signals. Before examining the differential response of trading strategies to the informativeness of macro signals updated on the platform, I first confirm that macro signal updates are meaningful events for the strategies' trading activity, so that release-day turnover can be used as a proxy to reveal signal adoption. I test whether macro release days predict greater trading activity overall, and confirm this is indeed the case. Relatedly, I conduct a placebo analysis on trading strategies that were entered into earlier trading contests when macro indicators were *not* available and, as expected, do not find any significant responses on the same calendar days. Next, I measure the sensitivity of each trading strategy's activity to the release of macro signals on the platform, and confirm that trading strategies with a similar level of macro signal sensitivity also show greater similarity in trading volume overall. These various analyses are described in Internet Appendix F.1.

4.2 Adoption of Informative Predictive Signals

I now analyze the responses of contestants' systematic trading strategies to the predictive informational content released when macro signals are updated on the Quantiacs platform.

Following Eqn. (1), I calculate daily turnover measures for a trading strategy i, then standardize these volume values at the strategy level; i.e. each strategy i has a mean turnover of zero, and units in daily standard deviation. Given my focus on differential responses to macro release days with varying levels of informativeness, I select the subset of daily turnovers that correspond to macro release days; i.e. I analyze days τ when the values of (one or more) macroeconomic signals were updated on the Quantiacs platform. Using this sample, I conduct regressions of the following form:

$$\begin{aligned}\text{Volume}_{i,\tau} = \beta_1 \times \text{Experienced}_{i,t} + \beta_2 \times \text{Informativeness}_\tau \\ + \beta_3 \times \text{Experienced}_{i,t} \times \text{Informativeness}_\tau + \phi_t + \epsilon_{i,t,\tau}\end{aligned} \tag{8}$$

As the daily volume standardization step includes demeaning each strategy's daily turnover,

this is similar to including strategy fixed effects that control for any trading strategy-level unobserved variables (including unobserved investor skill) that might confound an analysis. Another benefit to the standardization step is that turnover magnitudes are made to be comparable across strategies – in units of strategy turnover standard deviations (i.e. z-scores) – and thus data from multiple strategies can be pooled together in a single regression. The aggregate informativeness of macro release days, $\text{Informativeness}_\tau$, is calculated according to Eqn. (7). I take care to compute the informativeness index using only data up to the end of the year *before* the beginning of the live period of the current contest t. This ensures the informativeness measure does not contain information that was unavailable to Quantiacs participants at the time of the contest. Model year fixed effects ϕ_t control for different mean values of the informativeness measure that correspond to such different endpoints. A dummy for experience takes the value 1 if the human investor who implemented the strategy is taking part in her third (or higher) contest at that point.

[Insert Table 4 here]

Table 4 presents regression results for (standardized) daily turnover on macro release days against the aggregate information content of these macro release days. The first two columns show baseline results. Column (1) shows a positive and significant value for the β_1 coefficient when it is estimated alone, indicating that experienced investors design trading strategies that trade more than usual on macro release days. Column (2) shows a positive and significant estimate of β_2 when it is estimated alone, indicating that investors design trading strategies that tend to respond more strongly to the release of more informative macro variables; this estimate does not break out experienced and inexperienced investors.

The estimates from the full specification in column (3) show that experienced and inexperienced investors' trading strategies respond differently to the information content of macro release days. The estimate of $\widehat{\beta}_2 = 0.6348$ suggests that inexperienced investors design trading strategies that respond more to more informative macro release days, but the effect is only marginally significant. As for experienced investors, the estimates for the baseline coefficient of $\widehat{\beta}_1 = -0.3229$ and interaction effect of $\widehat{\beta}_3 = +1.025$ suggest that experienced investors respond less strongly to completely uninformative macro variable release days, and respond more strongly to more informative macro release days. Novices' strategies show a weak and noisy response to informativeness, whereas experienced investors' strategies display a much stronger and statistically clearer sensitivity to informative macro release days.

I conclude that experienced investors make better use of informative predictive variables than inexperienced investors do when specifying predictive trading strategies. This occurs

despite both groups of contestants having the same opportunity to detect informative predictive variables in the controlled contest setting.

4.3 Adoption of Familiar Signals

Inexperienced investors respond only weakly to genuinely predictive macroeconomic signals, so their adoption decisions likely depend on other attributes.

A natural candidate is the familiarity or recognizability of a signal. For instance, the availability heuristic (Tversky and Kahneman, 1973, 1974) predicts agents over-weight options that come to mind easily. More broadly, one may interpret a reliance on familiar signals as either a behavioral bias, or simply that familiarity enters into an investor's priors. Under either interpretation, familiarity is a distinct criterion from signal informativeness.

In my setting, familiarity may serve as a default adoption margin while experience primarily shifts investors toward using informativeness; the prediction is then a broad familiarity response across experience levels.

4.3.1 Measuring Signal Familiarity

To proxy for how familiar a macroeconomic indicator k is perceived to be by participants, I count how frequently it is mentioned in different forms of media. Specifically, I count its frequency of appearance in (i) news articles indexed by Factiva, and (ii) published books indexed by Google Books. Both these databases allow me to search for occurrences of specific phrases in specific time periods, and I conduct annual searches for each of the 54 macroeconomic variables provided by the Quantiacs platform. These two comprehensive sources result in different (but correlated) counts for the number of mentions of each macroeconomic variable.

To calculate an aggregate familiarity index for each macroeconomic release date τ, fixing a data source and search period, I compute the aggregate familiarity of each macroeconomic indicator k among the set of macroeconomic indicators $\mathcal{R}(\tau)$ released together on date τ by the Quantiacs platform:

$$\text{Familiarity}_\tau = \frac{1}{\text{Total mentions}} \sum_{k \in \mathcal{R}(\tau)} \text{Mentions}(k). \tag{9}$$

Eqn. (9) measures the total share of media mentions of the subset of macroeconomic signals that is released by the Quantiacs platform at date τ. As described shortly, I match the annual period over which shares are computed to the corresponding trading contest when conducting my analyses.

Unlike my measure of macro release day informativeness, these aggregate familiarity indices are empirically concentrated, with the most familiar macroeconomic variables accounting for a large fraction of total media mentions; further details are provided in Internet Appendix D. Across the distinct sources, the two familiarity indices that I construct using Eqn. (9) are highly correlated with one another, with a magnitude of 0.79. The familiarity indices covary much less strongly with the index of macro release day informativeness, which has a correlation of only 0.15 and 0.21 with the familiarity indices derived from news articles and books, respectively. I use both macro release day familiarity indices in the subsequent analyses to ensure my results are not sensitive to any one source.

4.3.2 Reliance on Familiar Signals

I now analyze the responses of contestants' systematic trading strategies to investors' total familiarity with the variables released on macro release days. I prepare standardized daily trading strategy turnover values on macro release days, as in Section 4.2. Where i denotes a trading strategy, τ a macro release day, and t a trading contest, I conduct regressions of the following form, for each type of familiarity index:

$$\begin{aligned}\text{Volume}_{i,\tau} = \beta_1 \times \text{Experienced}_{i,t} + \beta_2 \times \text{Familiarity}_{\tau} \\ + \beta_3 \times \text{Experienced}_{i,t} \times \text{Familiarity}_{\tau} + \phi_t + \epsilon_{i,t,\tau}\end{aligned} \tag{10}$$

When calculating familiarity indices using Eqn. (9), I take care to restrict my search of news article or book mentions to the year in which the end of the backtest (in-sample) period of the corresponding trading contest t falls; this ensures that I am measuring the familiarity of macro variables at the time investors are designing their trading strategies. Fixed effects for these benchmark periods ϕ_t absorb any variation in the annual means of familiarity indices. Note that daily volume is standardized (i.e. a z-score) as before, which once again implicitly controls for strategy-level (and investor-level) unobserved heterogeneity, and allows samples to be pooled across strategies.

[Insert Table 5 here]

Table 5 presents regression results of daily strategy turnover against the aggregate familiarity of those macroeconomic signals being released to investors. The estimated coefficient $\widehat{\beta}_2$ takes approximately the same value across all specifications; that is, whether an interaction with investor experience is incorporated or not, and whether the measure of aggregate familiarity is computed based on news article or book mentions. All estimates for $\widehat{\beta}_2$ are significantly non-zero at the 99% level. By contrast, none of the estimates for $\widehat{\beta}_3$, the interaction effect be-

tween familiarity and experience, are significantly different from zero; the evidence thus points to a broad familiarity response. Familiarity's role as a default heuristic for novices arises from the contrast with informativeness: novices show weak sensitivity to predictive content, while experienced investors additionally respond to genuine informativeness.

[Insert Table 6 here]

Table 6 augments the previous regressions to include the index of macro release day predictive informativeness, as well as an interaction with experience. All estimates are of a similar sign and significance to those in the separate informativeness regressions (Table 4) and familiarity regressions (Table 5). Neither index drives out the other, supporting the interpretation that familiarity is not merely a proxy for informativeness; it is a separate adoption margin. This result re-emphasizes familiarity as a distinct criterion that differs from informativeness.

5 Differential Gains from Signal Availability

Differential signal adoption should be reflected in performance outcomes: since experienced investors respond more strongly to informative signals, the gains from having such signals available should accrue disproportionately to them. I first bring signal informativeness into the performance regressions directly, and find that experience and informativeness interact: experienced investors earn incrementally higher returns from the most informative signals. I next compare the experience–performance gradient across information environments, before and after macro signals became available, and find that the gains from access to the additional predictors are concentrated among experienced investors, while novices derive no benefit. The section closes by testing alternative explanations for the experience gradient.

5.1 Returns Earned After Macro Release Day Rebalancing

To measure the gains derived from the availability of macro signals of varying informativeness, Table 7 shows the results of panel regressions of the form

$$\begin{aligned}\text{Post-Update Return}_{i,\tau} = {} & \beta_1 \times \text{Informativeness}_{\tau} + \beta_2 \times \text{Experienced}_{i,t} \\ & + \beta_3 \times \text{Informativeness}_{\tau} \times \text{Experienced}_{i,t} + \beta_4 \times \text{Familiarity}_{\tau} + \pi_i + \phi_t + \epsilon_{i,t,\tau}, \quad (11)\end{aligned}$$

in which the dependent variable is the cumulative return earned by a trading strategy on all the days between the updating of macro variables on the Quantiacs platform. The sample is limited to trading strategies entered into later contests in which the macro signals are available. Other variables are defined as in the previous section, including the model/benchmark year

time effects ϕ_t. Since the dependent variable is a cumulative return, I do not standardize it and instead make use of a contestant-level fixed effect π_i.

[Insert Table 7 here]

The baseline estimates for β_1 are positive, although significance depends on the specification: for inexperienced investors, more informative macro release days τ appear to predict higher returns immediately after trading strategies have rebalanced to incorporate this information. Importantly, the positive and significant estimates for β_3 show that trading strategies designed by experienced investors enjoy an incrementally higher benefit from informative macro signals. Combined with the negative β_2 estimates, this pattern indicates experienced investors' returns are concentrated in the periods following the release of the most informative macro release days τ. Since $\beta_2 + \beta_3 > 0$, a positive experience–performance gradient is apparent in this analysis. The negative and significant estimates of β_4 are consistent with those strategies reliant on familiar signals suffering from lower returns post-release.

5.2 Experience–Performance Gradients Across Information Environments

To assess whether the availability of macroeconomic predictors changes the experience--performance gradient, I compare contestant–contest observations from two information environments: Treatment observations are for contestants who participated only after macro signals became available on the Quantiacs platform; i.e., from contest 8 onwards. The Control sample consists of contestant–contest observations from contests 1–7; i.e., before the macroeconomic signals were added to the Quantiacs platform. These definitions ensure that, within the regression sample, each contestant's included competition history unfolded within a single, stable information environment. To be able to include fine-grained experience level indicators, the sample focuses on investors who have experienced up to four contests.

The regressions in Table 8 analyze the relationship between investor experience and the availability of additional predictive signals and the out-of-sample performance outcomes using various specifications. The indicator "Macro Signals Available$_t$" equals one for Treatment observations and zero for Control observations, as defined above. All specifications take performance outcomes to be the excess of the out-of-sample SR over the SR from holding the benchmark index, in order to permit valid comparisons across time periods.[11]

[11] Because Macro Signals Available$_t$ varies at the contest level, contest t fixed effects would absorb it. I therefore benchmark-adjust performance to account for common time-varying market conditions across contests. The benchmark portfolio consists of equally-weighted buy-and-hold positions in contestants' tradeable universe of futures contracts, as described in Internet Appendix E.

[Insert Table 8 here]

The regression results in Panel A of Table 8 are variants of the following linear specification:

$$\begin{aligned}&\text{Excess Live SR}_{i,t}\\ &\quad = \ \beta_1 \ + \ \beta_2 \times \text{Contests Experienced}_{i,t} \ + \ \beta_3 \times \text{Macro Signals Available}_t\\ &\qquad + \ \beta_4 \times \text{Contests Experienced}_{i,t} \times \text{Macro Signals Available}_t \ + \ \epsilon_{i,t}.\end{aligned} \tag{12}$$

The positive estimate of $\widehat{\beta}_4 = 0.908$ shows that the experience–performance gradient is steeper in contests held after the macroeconomic predictors were introduced than in earlier contests. The positive estimate of $\widehat{\beta}_2 = 0.589$ captures the baseline slope of performance with respect to experience in the pre-macro signal environment.

I also relax the assumption of a linear relationship between experience and performance by incorporating a dummy for every experience level, and find the effect continues to hold. The regression results in Panel B of Table 8 are variants of the following specification:

$$\begin{aligned}&\text{Excess Live SR}_{i,t}\\ &\quad = \ \beta_1 \ + \ \sum_{k=2}^{4}\left[\beta_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\}\right] \ + \ \gamma_1 \times \text{Macro Signals Available}_t\\ &\qquad + \ \sum_{k=2}^{4}\left[\gamma_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\} \times \text{Macro Signals Available}_t\right] \ + \ \epsilon_{i,t}.\end{aligned} \tag{13}$$

In Panel B, the interaction terms compare observations with the same experience level across the pre-macro signal and macro signal-available environments. The positive estimates for the higher-experience interactions $\widehat{\gamma}_3$ and $\widehat{\gamma}_4$ indicate that the performance advantage associated with the macro-available environment is concentrated among more experienced contestants. By contrast, lower-experience observations show little incremental benefit, with the estimates $\widehat{\gamma}_1$ and $\widehat{\gamma}_2$ not significantly differing from zero.

5.3 Alternative Explanations for the Experience Gradient

I attribute the observed experience–performance gradient to a learning-by-doing mechanism (Arrow, 1962). In this section, I entertain potential alternative explanations, which turn out not to find support in the data.

5.3.1 Attrition and Selection

I now examine whether the experience–performance gradient (and its steepening in the presence of macro signals) might be explained by a selection bias due to investor attrition. Such a selection bias could be due to low-ability investors being less likely to participate in subsequent trading contests (e.g., Seru, Shumway, and Stoffman, 2010). Variation in the strength of this selection bias across information environments could also be a concern: if contestants who would derive a strong benefit from learning-by-doing become more willing to participate in the presence of additional predictive signals, that may explain a steepening in the observed experience gradient in the later information environment.

On the other hand, the opposite form of selection is also possible in my trading contests setting. Low-ability investors might be more likely to persist (e.g., Linnainmaa, 2011). Similarly, the contestants who would benefit the most from incorporating additional predictive signals into their strategies might also be the least likely to continue to participate. Such forms of selection would bias OLS estimates of the experience–performance gradient downward.

A first, direct check is already contained in my main specification: the contestant fixed effects in Table 2 absorb any time-invariant, unobserved differences in contestant ability, so the experience–performance gradient is identified from within-contestant improvement.

As a complementary test, resting on a different identifying assumption, I next correct directly for selection into continued participation using a Heckman (1976) two-stage model, with standard errors computed according to Greene (1981). The first stage of the procedure consists of a probit model for the participation of the contestants in the next contest. In this stage, I include two covariates that most likely satisfy an exclusion restriction: the mean of the Google Search Index for "Quantopian"[12] and the *relative* number of entries that the contestant has made in the *prior* contest compared to the mean. The first-stage coefficients are shown in the top section of Table 9, and the estimates indicate that contestants are less likely to participate in the next contest as they gain in experience and as the rival trading platform (Quantopian) gains in attention. Contestants are also more likely to participate again if they have recently participated more intensively compared to others.

[Insert Table 9 here]

[12]Quantopian was one of Quantiacs' rival FinTech platforms for running trading contests (Fleiss, Kominers, and Ughetta, 2017; Zheng, 2017). The logic of my exclusion restriction is that the contestants on each platform may exhibit substitutability in which platform they participate in. Thus, search interest in and attention to a rival platform (Quantopian) could affect participation in my focal setting (Quantiacs). Note that the rival Quantopian platform became defunct (as announced on 29 October 2020) but was active throughout my sample period.

The second-stage coefficients represent the outcome equation of interest, and these are shown in the middle section of Table 9. The coefficient on experience is positive throughout, and statistically significant both overall (in column 1), and when conditioning on the availability of the new predictive variables (column 3). These findings are reassuring that the earlier results on learning with experience remain positive when accounting for potential selection into continued participation, for instance if investors are learning about their own types (Seru, Shumway, and Stoffman, 2010).

More importantly, in contests where macro signals are available (column 3) the coefficient on the Inverse Mills Ratio is negative and statistically significant, which implies a negative correlation ρ between the unobservables driving participation and those driving performance. The statistical significance of this term indicates that selection on unobservables is present, yet the negative sign implies that this selection biases estimates of the experience effect *downward*; that is, the bias works *against* finding a positive gradient. As a result, my main findings of a positive experience–performance gradient most likely understate the true effect, and are thus conservative.

5.3.2 Crash Risk

Because contest participants are assessed on their strategies' Sharpe ratios, one possibility is that the experience–performance gradient could reflect gaming of the metric: Goetzmann, Ingersoll, Spiegel, and Welch (2002) show that strategies bearing crash risk can inflate measured Sharpe ratios, so experienced contestants may simply have learned to load on such risk rather than to predict returns.

Internet Appendix G.1 examines this possibility and finds that trading strategy crash risk is decreasing (not increasing) in the experience level of the investor. Furthermore, there is no statistically significant relationship with the magnitude of returns in the lower tail of the daily return distribution or with the skewness of the distribution.

5.3.3 Competition

In a rank-order contest, competitive intensity could in principle alter contestants' willingness to exploit available signals through additional effort: facing a larger field of rivals, a contestant has a sharper incentive to develop and refine more strategies, which could raise both her performance and her use of the available signals.[13] Because competitive intensity may have

[13]This is distinct from a price-impact channel: an advantage of the Quantiacs setting is that one participant's trading does not move asset prices for another, eliminating strategic behavior that operates through prices. The potential concern here operates instead through relative ranking and effort.

risen over my sample as the Quantiacs platform became better known, such an effort response is a potential confound for the experience–performance gradient.

Two features of my analysis address this concern directly. First, competitive intensity is a contest-level attribute: every contestant in a given contest faces the same field of rivals. It is therefore fully absorbed by the contest fixed effects in my main specifications (Table 2).

Second, the effort channel itself finds no empirical support: Internet Appendix G.2 measures competitive intensity by the number of contestants in a contest, and finds that it has no significant relationship to a contestant's own number of entries into that contest.

5.3.4 Accumulated Entries

Because a contestant's performance is measured by her best live entry, one potential concern is that the experience–performance gradient could simply be a mechanical artefact: a contestant who submits more strategies, or resubmits a larger stock of past ones, might obtain a higher maximum simply by taking more draws, and experienced contestants may accumulate larger stocks of trading strategies from past contests that could be resubmitted to future contests.

Although contestants are permitted to submit multiple entries, Table 1 shows that the overall median number of entries in a contest is only 1 entry per contestant, which partly mitigates this concern.

Furthermore, the analysis in Internet Appendix G.3 addresses the concern more directly by adding two effort controls to the main specification: the number of entries in the current contest, and the stock of prior entries, which captures the size of the resubmittable pool. More entries do raise the best live Sharpe ratio, with a positive and significant coefficient, just as a mechanical account would predict. However, the coefficient on experience remains significant, positive, and of the same order of magnitude as the controls are added. The experience–performance gradient is therefore distinct from the mechanical effect of accumulating a larger stock of trading strategies over time.

6 Modeling Behavioral Frictions in Signal Adoption

The evidence so far documents a learning friction in signal adoption that erodes with experience, as well as a signal-specific familiarity bias. To interpret such behavioral frictions in a unified framework, I now present a model for an investor's prediction problem that incorporates a bias against adopting valid signals, which operates as a penalty on signal use. Estimating

the model at the trading strategy level, I decompose the penalty into a signal-specific familiarity component and a general subjective component; the general component declines with experience, matching the reduced-form gradient. Finally, I examine equilibrium implications: specializing to a single signal, I endow investors with heterogeneous biases and show that their under-adoption can generate return predictability.

Internet Appendix A contains all proofs for this section.

6.1 An Investor's Prediction Problem

Consider an investor who faces a prediction problem (Martin and Nagel, 2022) when determining her demand for an asset. She is endowed with m signals $s_1, s_2, \ldots, s_m$ that can be used to produce a prediction $\widehat{y}$ for some quantity y (such as a payoff) whose conditional mean is linear in the predictive signal values,

$$y = \sum_{i=1}^{m} b_i s_i + \varepsilon = \boldsymbol{s}\boldsymbol{b} + \varepsilon, \qquad \mathbb{E}[\varepsilon \mid \boldsymbol{s}] = 0, \tag{14}$$

where row vector $\boldsymbol{s}$ collects signal values, column vector $\boldsymbol{b}$ contains linear coefficients, and ε is unpredictable noise.

These parameters $\boldsymbol{b}$ are unknown, and so the investor forms estimates based on n previous realizations of (14), each of which relates a past realized payoff y of a related asset, generated with the same coefficients $\boldsymbol{b}$, to the corresponding prior signals available $s_1, s_2, \ldots, s_m$ at the time.[14] Arrange these n sets of historical samples in n-dimensional column vectors $\boldsymbol{y}$ and $\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_m$, respectively. For convenience, define the $n \times m$ data matrix $\boldsymbol{S} \triangleq [\boldsymbol{s}_1 \;\; \boldsymbol{s}_2 \;\; \ldots \;\; \boldsymbol{s}_m]$. Then the investor's prediction problem requires her to determine the values of these unknown parameters based on the historical data that she observes. Defining $\mathrm{Err} : \mathbb{R}^n \times \mathbb{R}^n \to [0, +\infty)$ as some measure of error or deviance between its arguments, her objective during the model estimation process will be to minimize the error between the observed historical outcomes $\boldsymbol{y}$ and her predictions based on the historical signal values $\boldsymbol{S}$:[15]

$$\min_{\boldsymbol{b} \in \mathbb{R}^m} \mathrm{Err}(\boldsymbol{y}, \boldsymbol{S}\boldsymbol{b}) \tag{15}$$

[14] In the Quantiacs setting, the investable universe comprises multiple futures contracts of a fixed maturity that are derivatives of the same underlying asset; e.g., CME S&P 500 E-mini futures contracts mature quarterly.

[15] For instance, an investor seeking to maximize the out-of-sample Sharpe ratio of a portfolio (as incentivized by the Quantiacs setting) must estimate an asset's expected return, which is itself a prediction problem. For the closely-related Markowitz (1952) portfolio choice problem, Best and Grauer (1991) showed analytically that both over- and under-estimating assets' expected returns are errors.

Below, $||\cdot||_1$ and $||\cdot||_2$ are the ℓ_1/taxicab and ℓ_2/Euclidean norms of a vector, respectively.

6.1.1 Frictionless Baseline

As a baseline (e.g., Martin and Nagel, 2022), consider an investor who estimates $\boldsymbol{b}$ using

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} ||\boldsymbol{y} - \boldsymbol{S}\boldsymbol{b}||_2. \tag{16}$$

The solution $\widehat{\boldsymbol{b}}$ to this baseline prediction problem (16) is given by ordinary least squares (OLS). Importantly, $\widehat{\boldsymbol{b}}$ does not depend on any investor-specific attributes: any investors with an identical historical dataset $(\boldsymbol{y}, \boldsymbol{S})$ will arrive at an identical estimate for $\widehat{\boldsymbol{b}}$, assuming the OLS problem is not under-determined. Thus, this baseline cannot rationalize observed empirical heterogeneity in the predictions of investors who have identical datasets (seen in Tables 1 and 2) without incorporating additional frictions into an investor's prediction problem.

6.1.2 Incorporating Behavioral Frictions

I now introduce a tractable form of behavioral frictions that impede investors' willingness to adopt predictive signals. The key model ingredient is for the investor to face a subjective penalty or aversion to incorporating signals into her prediction. Expressing a bias toward familiar signals is one important example, and prior work by Cao, Han, Hirshleifer, and Zhang (2011) in a portfolio choice setting models unfamilarity through a fear of worst-case outcomes. With this motivation in mind, I define a *biased* investor as one subject to the following frictions:

Definition 1. *A biased investor determines the unknown parameters $\boldsymbol{b}$ in the prediction problem* (15) *by considering the worst-case error that may result for any given choice of parameter values,*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \max_{\boldsymbol{U}\in\mathcal{U}} ||\boldsymbol{y} - (\boldsymbol{S}+\boldsymbol{U})\boldsymbol{b}||_2, \tag{17}$$

where $\boldsymbol{U}$ is a matrix of signal-wise perturbations that maximizes the ℓ_2 norm-based error for any choice of $\boldsymbol{b}$ and is constrained by the set

$$\mathcal{U} \triangleq \left\{ [\, \boldsymbol{u}_1 \;\; \boldsymbol{u}_2 \;\; \cdots \;\; \boldsymbol{u}_m \,] \,:\, \|\boldsymbol{u}_j\|_2 \leq \rho_j \;\; \forall\, j = 1, \ldots, m \right\}, \tag{18}$$

that is characterized by a set of variable-specific upper bounds $\rho_j \geq 0$, perceived by the investor, on the ℓ_2 norm of each possible signal-wise disturbance $\boldsymbol{u}_j$.

Distortions up to signal-specific bounds of radius ρ_j can capture signal-specific frictions

such as relative familiarity, as well as overall frictions affecting the investor. The following proposition characterizes the solution to the biased investor's prediction problem:

Proposition 1. *Fix any vector of bounds* $\{\rho_j\}$ *in* (18)*, let* $\widehat{\boldsymbol{b}}$ *solve* (17)*, set* $\widehat{\kappa} \triangleq \|\boldsymbol{y} - \boldsymbol{S}\widehat{\boldsymbol{b}}\|_2$ *(its residual norm), and assume* $\widehat{\kappa} > 0$*. Then every solution of*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \tfrac{1}{2}\|\boldsymbol{y} - \boldsymbol{S}\boldsymbol{b}\|_2^2 + \sum_{j=1}^{m} \delta_j |b_j|, \qquad \delta_j \triangleq \widehat{\kappa}\,\rho_j, \tag{19}$$

solves (17)*; and, in the other direction,* $\widehat{\boldsymbol{b}}$ *itself solves* (19).

Under relatively mild technical conditions, the solution to (19) is unique (Tibshirani, 2013).

Each formulation of the investor's prediction problem offers a different view onto the range of behavioral frictions it can capture. The formulation in Definition 1 connects directly to familiarity: the bounds ρ_j encode the investor's fear of worst-case signal perturbation, in the spirit of Cao, Han, Hirshleifer, and Zhang's (2011) treatment of unfamiliarity in portfolio choice. The penalized problem (19) connects to bias more generally: whatever its source, an aversion to adopting signals operates as a penalty that shrinks their weights, without commitment to any particular microfoundation. Because the penalties are signal-specific, their variation across signals within an investor can capture relative familiarity, while their overall level captures frictions operating at the level of the investor herself.

The functional form of (19) connects the model to Gabaix's (2014) theory of sparsity-based bounded rationality, with one difference being that I allow the penalties $\{\delta_j\}$ to differ across signals j within an investor, rather than imposing uniform penalization. As in Gabaix (2014), the solution may be sparse. A biased investor may therefore discard valid signals entirely, in line with evidence that decision-makers can ignore available information in other domains (Hanna, Mullainathan, and Schwartzstein, 2014; Bastianello, Décaire, and Guenzel, 2024).

The parameter $\delta_j = \widehat{\kappa}\,\rho_j$ is a rescaling of the bound ρ_j by the residual scale of the selected solution. I will later take δ_j to be a behavioral primitive; first, I show it is interpretable as a bias. The frictionless problem (16) is solved by OLS; a positive penalty shrinks the biased investor's coefficients away from that benchmark and against adopting signals. The following corollary to Proposition 1 highlights that this is interpretable as a bias against specific signals.

Corollary 1. *In the setting of Proposition 1, fix a solution* $\widehat{\boldsymbol{b}}$ *of* (17) *with residual norm* $\widehat{\kappa} > 0$ *and associated parameters* $\delta_j = \widehat{\kappa}\,\rho_j$*, and assume the signals are orthonormal:* $\boldsymbol{S}^T\boldsymbol{S} = \boldsymbol{I}$*. Then* $\widehat{\boldsymbol{b}}$

is the unique solution of (19) *and the biased investor predicts*

$$\widehat{y} = \boldsymbol{s}\widehat{\boldsymbol{b}}, \tag{20}$$

where $\boldsymbol{s}$ *is an m-dimensional row vector consisting of the m predictive signals and* $\widehat{\boldsymbol{b}}$ *is an m-dimensional column vector of signal loadings consisting of elements*

$$\widehat{b}_k = \text{sign}(\boldsymbol{s}_k^T \boldsymbol{y}) \max\left\{|\boldsymbol{s}_k^T \boldsymbol{y}| - \delta_k, 0\right\}. \tag{21}$$

Corollary 1 highlights several implications of behavioral frictions for an investor's adoption of predictive signals: (i) Over the region $|\boldsymbol{s}_k^T \boldsymbol{y}| \leq \delta_k$ of the input domain, a biased investor will entirely ignore a predictive variable k by choosing the weighting parameter $\widehat{b}_k = 0$. The model therefore allows for the possibility that one or more predictive signals are completely excluded from the investor's prediction. The model thus captures the potential for sparsity (Gabaix, 2014) in signal adoption. (ii) The larger the magnitude of the investor's bias δ_k against variable k, the larger its historical predictive contributions should be in order to surmount the threshold δ_k and enter into the investor's predictions (and ultimately actions) with non-zero weight. (iii) Even signals that enter with a positive weight are underweighted, by an offset δ_k. Thus the model captures a milder form of underweighting as well as allowing for a total lack of adoption. (iv) The term $\boldsymbol{s}_k^T \boldsymbol{y}$ in Equation (21) is the OLS solution to an unbiased investor's prediction problem (e.g., Martin and Nagel, 2022). The full expression thus characterizes the distortion induced by a behavioral friction in comparison to a frictionless benchmark. The next corollary further characterizes signal loadings.

Corollary 2 (Signal loadings vs. informativeness & bias). *Under the orthonormality of Corollary 1, let the signal loadings* $\widehat{\boldsymbol{b}}$ *solve* (19) *with signal-specific penalties* $\delta_k > 0$*, and orient each signal so that its benchmark contribution is nonnegative,* $x_k \triangleq \boldsymbol{s}_k^\top \boldsymbol{y} \geq 0$ *(without loss of generality), so that* $\widehat{b}_k = \max\{x_k - \delta_k, 0\}$ *per* (21)*. Then:*

(i) At a fixed penalty δ_k*, the loading* $\widehat{b}_k$ *is nondecreasing in the contribution* x_k*, and strictly increasing wherever* $\widehat{b}_k > 0$*.*

(ii) At a fixed contribution x_k*, the loading* $\widehat{b}_k$ *is nonincreasing in the penalty* δ_k*, and strictly decreasing wherever* $\widehat{b}_k > 0$*.*

Corollary 2 can be interpreted in light of existing empirical findings. Part (i) relates signal loadings to informativeness: at a common penalty, an investor's predictions load more heavily on signals with larger historical predictive contributions x_k. Part (ii) speaks to familiarity bias:

the greater an investor's bias against incorporating a signal δ_k, the weaker her predictions load on this signal. If the penalty δ_k falls as an investor gains experience, then comparative static (ii) also accounts for an experience gradient in the adoption of an informative signal.

6.2 Empirical Test: Experience Gradient in the Common Signal Penalty

I now take the model to the data. This analysis tests whether the model's decomposition is more than an interpretation: if the penalty structure is right, the investor-level bias component λ should vary with experience, even when the available dataset is identical across investors.

The penalized problem (19) is estimable at the trading strategy level, and its penalty structure lets me separate the investor-level component of bias from the signal-specific familiarity component. To do so, I exploit the timeseries of daily returns from the Quantiacs contests.

Estimating the investor-specific problem (19) requires empirical values for outcomes $\boldsymbol{y}$ and signals $\boldsymbol{S}$. I interpret $\boldsymbol{y}$ as expected returns and proxy for these using the timeseries of daily portfolio returns earned by the investor.[16] I define a corresponding matrix of 934 predictive signals $\boldsymbol{S}$ that the investor had access to at the time of forming her daily portfolio: the latest available 5 daily returns (i.e. lags 1 to 5) and their squares (proxying for a historical volatility signal), for each of the 88 futures contracts in the investor's tradeable universe, plus the latest available values (i.e. lag 1) of each of the 54 macro variables available to contestants. Predictive variables are standardized to a common scale. The signals I employ are, of course, only a subset of those an investor might possibly construct: daily price series could be combined into richer technical indicators, interacted with one another or with the macroeconomic variables. My deliberately parsimonious and transparent signal set makes this exercise a test of investor behavior over one economically reasonable slice of the signal universe, rather than an exhaustive characterization.

I estimate the investor-specific model (19) using the adaptive lasso (Zou, 2006):

$$\widehat{\boldsymbol{b}}_{i,t} \;=\; \underset{\boldsymbol{b}}{\operatorname{argmin}} \; \tfrac{1}{2}\left\|\boldsymbol{y}_{i,t} - \boldsymbol{S}_{i,t}\,\boldsymbol{b}\right\|_2^2 \;+\; \lambda_{i,t} \sum_j w_{j,t}\,|b_j|, \tag{22}$$

The estimation is run once per trading strategy timeseries, on contests where both price-based and macro signals were available to participants.

As Eqn. (22) shows, all bias parameters $\delta_{i,j,t}$ are factorized as $\delta_{i,j,t} = \lambda_{i,t} w_{j,t}$, where i represents the contestant, t the trading contest, and j the signal. This factorization operationalizes

[16] In this regard, I follow a very large literature in empirical asset pricing that uses *ex post* returns to proxy for *ex ante* return expectations; for example, when testing factor models or other asset pricing models.

the decomposition of the penalty: the weights $w_{j,t}$ fix the signal-specific familiarity component using the text-based familiarity measures of Section 4.3, so that the estimated level $\lambda_{i,t}$ isolates the investor-level subjective component. Concretely, the weights are set to $w_{j,t} = 1$ (neutral) for price-based signals, and decreasing in familiarity for macroeconomic signals: for these macro signals, the weight follows a power law in the signal's share of news article-based familiarity, $w_{j,t} \propto s_{j,t}^{-1/\sigma}$, where σ is the dispersion pooled across baseline years. The overall penalty level $\lambda_{i,t}$ is estimated by 10-fold cross validation.

As well as the estimated penalties $\widehat{\lambda}_{i,t}$, I measure the number of non-zero estimated coefficients $\widehat{b}_{i,j,t}$, which captures the extensive margin of signal adoption (i.e., inclusion or exclusion). Table 10 shows that both quantities disperse widely across investors within a contest: the heterogeneous use of identical data documented in reduced form reappears as heterogeneity in the model's estimated bias parameters.

[Insert Table 10 here]

Table 10 shows that the estimated cross-signal investor-specific behavioral penalty $\widehat{\lambda}_{i,t}$ at a particular point in time varies with the investor's experience, in the direction that one should expect: experienced investors carry a lighter penalty (lower $\widehat{\lambda}_{i,t}$), and therefore adopt a larger number of macroeconomic indicators. Because the signal-specific familiarity weights are held fixed by construction, experience erodes the investor's general bias against signal use rather than her attitude toward particular signals. This result highlights that learning by experience is an investor-level mechanism: as an investor gains in experience, she approaches the behavior of an unbiased investor, captured by a decline in $\widehat{\lambda}_{i,t}$.

The number of adopted macro signals $\widehat{b}_{i,j,t} > 0$ is a measure of the complexity of investors' predictive models. Under this interpretation, the estimate in Table 10 column (2) reveals not only a sparsity in decision-makers' inputs (as in Hanna, Mullainathan, and Schwartzstein (2014) and Bastianello, Décaire, and Guenzel (2024)) but also a tendency for inexperienced investors to specify less complex models (Oprea, 2020; Puri, 2025).

The estimated penalties confirm the model's applicability as an overarching framework for the reduced-form results uncovered prior to this section.

6.3 Signal Adoption and Return Predictability

Next, I investigate the impact on return predictability of behavioral frictions that impede individual investors' adoption of predictive signals. A classic noisy rational expectations equilibrium (REE) model (Grossman and Stiglitz, 1980; Hellwig, 1980) with a single-signal single-

asset economy is sufficient to demonstrate the mechanism.

Asset Payoff and Signal. The asset's terminal payoff is

$$v = \bar{v} + b\,s + \varepsilon, \qquad s \sim \mathcal{N}(0,1), \quad \varepsilon \sim \mathcal{N}(0,\sigma_\varepsilon^2), \quad s \perp \varepsilon. \tag{23}$$

Here $\bar{v}$ is the mean payoff, s is the standardized signal (the scalar counterpart of Section 6.1's current signal values $\boldsymbol{s}$), $b > 0$ (without loss of generality) is the signal's informativeness or loading, and ε is unpredictable noise. $b\,s$ is the component of the payoff that is predictable by the signal, which I term the signal's *content*. The signal enters the specification through the payoff v in order to isolate the role of the equilibrium price p in determining the asset's realized return $v - p$.

Investors and Signal Adoption. The market is populated by a unit continuum of investors indexed by $i \in [0,1]$, each maximizing CARA utility over terminal wealth with common risk aversion γ and trading the asset against a riskless numéraire whose return is normalized to zero. As is standard for CARA investors, their demands q_i are return forecasts scaled by precision and risk tolerance, thus every investor forms a return forecast.

Every investor i carries a bias parameter $\delta_i \geq 0$ that captures behavioral frictions, as in Proposition 1, and here the bias parameter itself is the primitive. Parameters δ_i vary across investors, with a cross-sectional distribution taken as given for now; $\mathbb{E}_i[\cdot]$ denotes the cross-investor average, and $\mathbb{P}$ is with respect to the cross-sectional distribution. To be exact: each investor i is a biased investor in the sense that she forecasts the payoff with the population counterpart of the prediction problem (19), choosing the coefficient θ on the signal to solve

$$\min_{\theta \in \mathbb{R}} \; \tfrac{1}{2}\,\mathbb{E}\big[(v - \bar{v} - \theta s)^2\big] \;+\; \delta_i\,|\theta|. \tag{24}$$

Lemma 1 (Investors' signal loadings). *The unique solution of* (24) *is* $\theta_i^* = \max\{b - \delta_i, 0\}$.

The pair (b, θ_i^*) is the population counterpart of the true coefficients and estimated signal loadings $(b_k, \widehat{b}_k)$ of the biased investor's finite-sample prediction problem.[17]

[17]The precise relationship is in the limit: for signals standardized so that $\boldsymbol{S}^\top \boldsymbol{S}/n \to \boldsymbol{I}$, the solution of (19) converges in probability, coordinate by coordinate, to a soft-thresholded population coefficient of exactly the form in Lemma 1, with thresholds proportional to the limits of δ_k/n (Knight and Fu, 2000). Note that this scaling distinguishes the behavioral friction from statistical regularization: penalty sequences of order $o(n)$, including the $\sqrt{n \log m}$ rate that is optimal for estimation-error control (Bickel, Ritov, and Tsybakov, 2009), deliver zero thresholds and consistent estimates of the b_k, unlike the current model.

The signal s thus enters an investor i's return forecasting model at the coefficient $\max\{b - \delta_i, 0\}$, distorted from the true coefficient b, and so investor i trades on the fraction

$$\phi_i \triangleq \max\{b - \delta_i, 0\}/b = \max\{1 - \delta_i/b, 0\} \in [0, 1] \tag{25}$$

of the signal's content. An *adopter* is an investor with $\phi_i > 0$, equivalently $\delta_i < b$; an adopter's forecast conditions on s. For *non-adopters*, $\phi_i = 0$ because $\delta_i \geq b$. The cross-investor distribution of weights $\{\phi_i\}$ is taken as given for now, and later endogenized, as is standard in the REE literature. The equilibrium will depend on individual $\{\phi_i\}$ (and thus $\{\delta_i\}$) only via the aggregate *adoption fraction* a and the *effective adoption* Φ:

$$a \triangleq \mathbb{P}(\delta_i < b) \in [0, 1], \tag{26}$$

$$\Phi \triangleq \mathbb{E}_i[\phi_i] = a\,\bar{\phi} \leq a, \text{ with } \bar{\phi} \triangleq \mathbb{E}_i[\phi_i \mid \phi_i > 0]. \tag{27}$$

Since $\phi_i > 0$ exactly on $\{\delta_i < b\}$, the aggregates vanish together: $\Phi > 0$ if and only if $a > 0$. For tractability, the distortion is kept to the mean: an adopter's perceived payoff variance is constant at σ_ε^2.

Equilibrium is a noisy REE in the tradition of Grossman and Stiglitz (1980) and Hellwig (1980): each investor's demand is optimal given her information and forecasts, the price clears the market, and the price function investors use for inference is the one their trading generates. The friction's domain is the set of predictive signals an investor feeds into her model, and the market price lies outside it: the price of the asset she trades is familiar to every participant, and every investor conditions on it without friction. Adopters trade on the signal directly; non-adopters, whose own model specification excludes s, learn about the signal's content from the familiar price, as Bayesians. Adopters do not additionally condition on the price.[18]

Per-capita supply is random, $Z \sim \mathcal{N}(\bar{Z}, \sigma_Z^2)$, and is independent of s and ε, so the price is not fully revealing. In the linear equilibrium to be derived below, $p = p_0 + \pi\, bs - \Lambda Z$, with $\pi \in [0, 1]$ being the share of the signal's content impounded into the price. Observing p is thus equivalent to observing the statistic $\Psi \triangleq (p - p_0)/\pi = bs - \xi Z$; i.e., the signal's content plus supply noise scaled by $\xi \triangleq \Lambda/\pi$. The equilibrium constants are determined in the order of: the noise scale ξ, the precision τ_q of Ψ about the signal's content, the Bayes weight β_q that Ψ earns, and the resulting posterior payoff precision τ_N.

[18] The price is a function of (s, Z), and given s its residual variation reflects only the payoff-irrelevant supply, so conditioning on both s and the price is redundant for an unbiased adopter. The assumption maintained here is that a biased adopter likewise trades on the coefficient of Lemma 1 alone, without revising it through the price.

Proposition 2 (Equilibrium price and expected return). *Let $a > 0$. Market clearing $\int_0^1 q_i \, di = Z$ admits a linear equilibrium $p = p_0 + \pi \, bs - \Lambda Z$, unique in the linear class, with constants, in order of determination,*

$$\xi = \frac{\gamma}{\tau_A \Phi}, \qquad \tau_q = \frac{1}{\xi^2 \sigma_Z^2} = \frac{\tau_A^2 \Phi^2}{\gamma^2 \sigma_Z^2}, \qquad \beta_q = \frac{\tau_q}{\tau_q + \tau_\mu}, \qquad \tau_N = \left(\sigma_\varepsilon^2 + (\tau_\mu + \tau_q)^{-1}\right)^{-1}, \quad (28)$$

$$\pi = \frac{\tau_A \Phi + (1-a)\,\tau_N \,\beta_q}{M} \in [0,1], \qquad \Lambda = \pi \, \xi, \qquad p_0 = \bar{\nu} + \frac{(1-a)\,\tau_N \,\beta_q \,\xi \,\bar{Z}}{M}, \qquad (29)$$

where $\tau_A \triangleq 1/\sigma_\varepsilon^2$ is an adopter's perceived payoff precision, $\tau_\mu \triangleq 1/b^2$ the prior precision of the signal's content bs, τ_q the precision of the price statistic Ψ about the signal's content, τ_N a non-adopter's posterior payoff precision, and $M \triangleq a\,\tau_A + (1-a)\,\tau_N$ aggregates risk-bearing capacity; and the expected return conditional on the signal is

$$\mathbb{E}[v - p \mid s] \;=\; \frac{\gamma \bar{Z}}{M} \;+\; (1-\pi)\, b\, s. \qquad (30)$$

The equilibrium given by Proposition 2 behaves as one would expect. Price informativeness, the precision τ_q of the price statistic Ψ about the signal's content, rises with adoption: since $\xi = \gamma/(\tau_A \Phi)$, (28) gives $\tau_q = \tau_A^2 \Phi^2/(\gamma^2 \sigma_Z^2)$, increasing in effective adoption, because greater aggregate weight trading on the signal pushes its content harder into the price relative to supply noise. In the limit $\Phi \to 0$ the price teaches nothing ($\tau_q, \beta_q \to 0$) and non-adopters fall back on their prior. Price informativeness is highest at full adoption and full weight, $\Phi = 1$, though the price stays noisy as long as $\sigma_Z > 0$.

Expected returns also take a standard form. Equation (30) splits the conditional expected return into a level and a slope: the level $\gamma \bar{Z}/M$ carries no signal and is the usual compensation for holding the mean supply $\bar{Z}$, priced by aggregate risk-bearing capacity M; the slope $(1-\pi)\, b$ is the share of the signal's informativeness that the price does not impound; i.e., a predictive regression of realized returns on the signal would recover $(1-\pi)\, b$. The comparative statics of π are as follows.

Proposition 3 (Predictability falls with effective adoption but survives full adoption).

(i) The price loading π is strictly increasing in effective adoption Φ at any fixed adoption fraction a; equivalently, the share of the signal's content left in the return, $1 - \pi$ (and with it the return's predictive slope $(1-\pi)\, b$ of Proposition 2), is strictly decreasing in Φ, with $1 - \pi \to 1$ as $\Phi \to 0$. Predictability is maximal when no weight trades on the signal.

(ii) At full adoption ($a = 1$, equivalently $\delta_i < b$ almost surely), the price impounds $\pi = \Phi =$

$1 - \mathbb{E}_i[\delta_i]/b$, *and the surviving predictive slope equals the average bias:* $(1-\pi)\,b = \mathbb{E}_i[\delta_i]$. *Whenever* $\mathbb{E}_i[\delta_i] > 0$, *full adoption does not eliminate predictability.*

Proposition 3 part (i) gives the intuition that one might expect: price informativeness and return predictability are two sides of the same margin, and both vary with effective adoption. Read over time, it offers a natural account of post-publication return decay (McLean and Pontiff, 2016): if adoption increases upon the publication of a signal, the measured return-predictive slope can fall even if the signal remains just as informative about an asset's payoff as before.

Proposition 3 part (ii) makes a sharper point. Because investor biases induce underweighting even among adopters, predictability can survive even when every investor uses the signal: at full adoption ($a = 1$) the surviving return-predictive slope equals the average magnitude of investor bias $\mathbb{E}_i[\delta_i]$. Signal adoption thus attenuates the predictive slope to the average magnitude of investor bias, rather than to zero.

The No-Adoption Benchmark. At $a = 0$ every investor excludes the signal, and the equilibrium is immediate. The price is a function of the supply alone; conditioning on it leaves each investor at her prior, with payoff precision $\tau_0 \triangleq (\sigma_\varepsilon^2 + b^2)^{-1}$, and market clearing gives

$$p \;=\; \bar{v} \;-\; \frac{\gamma}{\tau_0} Z\,, \qquad \mathbb{E}[v - p \mid s] \;=\; \frac{\gamma \bar{Z}}{\tau_0} \;+\; b\,s\,. \tag{31}$$

The predictive slope in the no-adoption benchmark (31) is the signal's full informativeness b, in agreement with the $\Phi \to 0$ limit of Proposition 3, where $(1-\pi)\,b \to b$.

Role of Investor Biases. The equilibrium of Proposition 2 takes the adoption aggregates (a, Φ) as given. I now go further and link equilibrium return predictability (the slope $(1-\pi)\,b$ of Equation (30)) to the behavioral primitive that generates it: the distribution of biases δ_i in the cross-section of investors. I begin by introducing assumptions on the structure of these frictions and their impact on adoption margins.

Assumption 1 (Structure of investor biases). *Investor biases factor as* $\delta_i = c\,\nu_i$, *where the constant* $c > 0$ *is a common magnitude, and the draws* $\nu_i \sim G$ *are from a distribution on* $[0, \infty)$ *with unit mean (a normalization) and are independent of b and c. Write* $T \triangleq b/c$ *for the adoption threshold; G is continuous at T and, where it exists, g denotes its density.*

Assumption 2 (Margin dominance). *A marginal increase in the common magnitude of investor*

biases c erodes effective adoption Φ at least B times as fast as it erodes the adopter fraction a:

$$-\frac{\partial \Phi}{\partial c} \geq B\Big(-\frac{\partial a}{\partial c}\Big), \tag{32}$$

$$\textit{where } B \triangleq \frac{\sigma_\varepsilon^2 \beta_q + (\tau_\mu + \tau_q)^{-1}}{\sigma_\varepsilon^2 + (\tau_\mu + \tau_q)^{-1}} = 1 - \frac{\sigma_\varepsilon^2 \tau_\mu}{\sigma_\varepsilon^2(\tau_\mu + \tau_q) + 1}, \tag{33}$$

evaluated at the given (b, c). Equivalently, at the adoption threshold,

$$a - \Phi \geq B\, g(T)\, T. \tag{34}$$

Assumption 2 ranks the two channels through which the common bias scale operates: a higher c shrinks the signal weights of continuing adopters (the intensive margin, $-\partial\Phi/\partial c$) and pushes marginal adopters out of the signal entirely (the extensive margin, $-\partial a/\partial c$), and the intensive response must be at least B times the extensive response. The passthrough $B \in (0,1)$ rises with price informativeness τ_q, and tends toward one as the price becomes fully revealing ($\tau_q \to \infty$); thus, the assumption is mild whenever price-readers are poor substitutes for exiting adopters. Alternatively, by (34), the assumption is mild when the adoption threshold T lies beyond the body of the type distribution, so that few investors are marginal.[19] Under these conditions, I now derive the relationship between return predictability and the common magnitude of investors' bias against the signal.

Proposition 4 (Greater bias increases return predictability). *Under Assumptions 1 and 2, for fixed informativeness b, with adopters biased on average ($a > \Phi$) and G admitting a density at the threshold, the signal's equilibrium return-predictability slope $(1-\pi)\,b$ of (30) is strictly increasing in the common magnitude c of investor biases:*

$$\frac{d\big[(1-\pi)\,b\big]}{dc} > 0. \tag{35}$$

Proposition 4 shows that the greater investors' bias against adopting a predictive signal, the more strongly that signal predicts returns. Through this channel, the investor-level frictions

[19] For example, consider exponentially distributed types: $\nu_i \sim \text{Exp}(1)$, therefore $g(T) = e^{-T}$, with $a = G(T) = 1 - e^{-T}$ and $\phi_i = 1 - \nu_i/T$, therefore $a - \Phi = \frac{1}{T}\big[1 - (1+T)\,e^{-T}\big]$. By substitution, one can show condition (34) holds whenever $e^T \geq 1 + T + B\,T^2$. When $B \leq \frac{1}{2}$ (i.e., price informativeness is low) this holds for every T, hence for every c. Even under the worst-case of a fully-revealing price, $B \to 1$, the condition holds for $c \lesssim 0.56b$; i.e., the common bias scale is permitted to reach half the signal's predictive loading. In general, one can show that for any type density g that is nonincreasing beyond some point, the condition holds for all sufficiently small c.

that this paper empirically examines go on to determine how much of a signal's predictability survives adoption in equilibrium.

7 Mutual Fund Portfolio Evidence on Signal Adoption

The trading-contest setting allowed me to cleanly identify behavioral frictions by controlling participants' information sets and incentives. I now turn to a second, complementary setting to establish external relevance: the common-stock portfolios of actively-managed mutual funds. Fund managers operate under institutional mandates, risk constraints, and team structures that could easily swamp individual-level learning effects; detecting an experience gradient in signal adoption in this environment is therefore a demanding test of the mechanism. Nevertheless, I detect an experience gradient in predictive signal adoption that is consistent with the trading contest evidence: experienced managers tilt their portfolios more strongly in the direction of genuine predictive signals.

7.1 Mutual Fund Data

Mutual Fund Portfolios and Characteristics. I obtain mutual fund holdings data at a quarterly frequency from the CRSP Mutual Fund Database. I begin the sample in 2008, when CRSP holdings coverage and reliability improve (Schwarz and Potter, 2016); an additional advantage of CRSP over other data sources such as 13-F filings is that it records both long and short positions, which allows me to confidently measure active portfolio tilts (described below). I focus on domestic equity funds, exclude incubating funds, and exclude index funds following standard practice (Ben-David, Li, Rossi, and Song, 2022).

All other fund characteristics – including the names of their managers and their histories managing the current and past funds – are obtained from the CRSP Mutual Fund Database. Internet Appendix B presents summary statistics for the mutual fund portfolios used in subsequent analyses, including the portfolio tilt measures that I describe shortly.

Stock Return-Predictive Signals. I obtain stock-level return predictors from the open-source database of Chen and Zimmermann (2022) (version 2.0). Their database contains 212 firm-level characteristics that have been shown to predict returns, 208 of which I am able to match to an academic publication date using a combination of the OpenAlex API and manual inspection. Internet Appendix H provides detailed definitions of these characteristics.

To measure the informativeness of these signals, my baseline approach is in the spirit of McLean and Pontiff (2016): from $t+1$ onwards I compute the mean returns of long–short port-

folios formed by sorting stocks on the signal, and conform to the portfolio sorts and weighting scheme used in the original academic publication (Chen and Zimmermann, 2022). This variable is an out-of-sample measure of informativeness from the standpoint of a fund manager at the end of quarter t. Internet Appendix B summarizes the empirical distribution of these measures of signal predictive power throughout the common sample period.

Portfolio–Signal Tilts. To measure whether a fund manager actively positions her portfolio in the direction implied by a given return-predictive characteristic, I construct a portfolio–signal tilt at a quarterly frequency. Let t index quarters, let c index a firm-level predictive characteristic, and let i index stocks. For each characteristic c and quarter t, I sort stocks into deciles using NYSE breakpoints and define $s_{c,i,t} \in \{1, \ldots, 10\}$ as stock i's decile rank. The decile ordering is chosen so that higher values of $s_{c,i,t}$ correspond to higher expected returns.

For a portfolio p, I define gross-normalized holdings weights

$$w_{p,i,t} = \frac{V_{p,i,t}}{\sum_i |V_{p,i,t}|},$$

where $V_{p,i,t}$ is the signed position value. Gross normalization makes exposures comparable across portfolios that differ in leverage and naturally accommodates short positions. I define the analogous market weight $w_{MKT,i,t}$ for the market portfolio.

Given these ingredients, I first measure a portfolio's exposure to the characteristic-based signal s_c as the holdings-weighted average of the signal values $s_{c,i,t}$:

$$\text{Portfolio Signal Exposure}_{p,c,t} \triangleq \sum_i w_{p,i,t}\, s_{c,i,t}. \tag{36}$$

The market's exposure to a signal is defined analogously using market capitalization-based weights $w_{MKT,i,t}$:

$$\text{MKT Signal Exposure}_{c,t} \triangleq \sum_i w_{MKT,i,t}\, s_{c,i,t}. \tag{37}$$

A portfolio's signal exposure alone conflates active positioning with a default exposure present in the market. I therefore define a portfolio's *signal tilt* as its excess exposure to the predictive signal relative to the market:

$$\text{Portfolio Signal Tilt}_{p,c,t} \triangleq \text{Portfolio Signal Exposure}_{p,c,t} - \eta_{p,t}\, \text{MKT Signal Exposure}_{c,t}, \tag{38}$$

where $\eta_{p,t} \triangleq \sum_i w_{p,i,t}$ is the portfolio's overall net directional exposure. For long-only portfo-

lios, which comprise the vast majority of mutual fund portfolios, $\eta_{p,t} = 1$. For a market-neutral long/short portfolio, $\eta_{p,t} = 0$.

In this way, Portfolio Signal Tilt$_{p,c,t}$ is a directional, relative proxy for active signal use: it is higher when the portfolio overweights stocks with higher signal ranks *beyond* any baseline exposure inherited from the market. This tilt measure is closely related to holdings-based characteristic-exposure measures used in Chan, Chen, and Lakonishok (2002), Lewellen (2011), and Lettau, Ludvigson, and Manoel (2018). Quarterly portfolio–signal tilts are computed for the period 2008-2023. Internet Appendix B summarizes the empirical distribution of these tilts across portfolios.

Tilts and Alpha. Before examining differential tilts to various signals within the same portfolio (Eqn. (38)), I first confirm that stronger tilts in the direction of return predictability predict improved fund performance. To run this portfolio-level test, I calculate a single aggregate portfolio tilt in the direction of return predictability:

$$\overline{\text{Portfolio Tilt}}_{p,t} \triangleq \frac{1}{N_t} \sum_{c} \text{Portfolio Signal Tilt}_{p,c,t}. \tag{39}$$

The above measure is the simple mean over all N_t publicly available signal tilts by a portfolio p at time t. The public availability of a signal c is determined using its associated academic paper's publication date (as in McLean and Pontiff (2016)) according to the OpenAlex database.

[Insert Table 11 here]

Table 11 shows that a higher aggregate tilt (Eqn. (39)) predicts a higher portfolio alpha over the following period, including when common time shocks are controlled for together with portfolio-level constraints and mandates. CAPM and Carhart (1997) 4-factor alphas are computed following Barber, Huang, and Odean (2016), using both gross-of-fee and net-of-fee returns. Given my focus on tilts in excess of the market portfolio's, the CAPM alpha is most appropriate, yet both measures show a positive predictive relationship. This validates portfolio–signal tilts as an economically meaningful proxy for predictive signal adoption: portfolios with stronger aggregate tilts earn higher subsequent alpha.

7.2 Tilts, Signal Informativeness, and Fund Manager Experience

In the trading contests setting, a key finding was that experienced investors become more willing to adopt genuinely informative signals. I test whether such an effect also applies to mutual fund managers by comparing their portfolio–signal tilts to the manager's experience

(based on the total length of time they appear in the CRSP Mutual Fund Database) and to my main measure of predictive signal informativeness.

[Insert Table 12 here]

Table 12 shows that experienced managers tilt more strongly toward informative signals than their less-experienced peers. The key coefficient is the interaction between manager experience and signal informativeness in column 2, which is positive and significant: the within-portfolio association between tilts and signal informativeness is higher for experienced managers. The positive and significant coefficient on manager experience in column 1 shows that a manager's willingness to tilt in the direction of return predictability increases with experience. The inclusion of a manager fixed effect controls for baseline, time-invariant levels of skill or specialization in different trading styles. Columns 3 and 4 show that the interaction effect is robust to the inclusion of more stringent fixed effects, including time effects. This pattern is difficult to reconcile with alternative explanations under which experienced managers exploit their tenure to enjoy the quiet life or become entrenched, but is consistent with learning-by-doing through accumulated experience.

The mutual fund evidence should nevertheless be interpreted with caution. Portfolio tilts may reflect institutional mandates, risk constraints, team decisions, or implementation costs that are not present in the trading contests. Moreover, the causal direction between signal adoption and signal informativeness is harder to isolate in a setting where broad adoption can itself affect anomaly returns. For this reason, I use the mutual fund setting to establish external relevance, while relying on the trading contests for sharper evidence on adoption mechanisms.

8 Conclusion

Investors endowed with identical datasets do not put them to identical use. I document two behavioral frictions in predictive signal adoption that drive this divergence. The first is a learning friction that erodes with experience: experienced investors respond more strongly to genuinely informative signals, capture the gains from signal availability, and converge in the predictive models they specify. Another friction that drives a wedge between signal adoption and signal informativeness is a bias toward familiar and recognizable signals.

The frictions I document slow the incorporation of public information into prices: even when signals are freely available and genuinely informative, behavioral frictions rather than rational constraints leave them unexploited. In the model, such bias sustains return predictability even when every investor adopts the signal. This may explain why the post-publication decline

in predictability (McLean and Pontiff, 2016) is only partial: behavioral frictions may limit arbitrage even after information becomes public.

More broadly, this paper contributes to understanding how economic agents use predictive information and high-dimensional modeling tools in practice. The value of predictive signals depends not only on their statistical properties but also on whether and how decision-makers incorporate them into their models. As predictive technologies and high-dimensional datasets become increasingly accessible, the binding constraint may be less the availability of tools and data than the human process of selecting, validating, and combining predictive signals.

References

Abis, S., & Veldkamp, L. (2024). The changing economics of knowledge production. *Review of Financial Studies*, *37*(1), 89–118.

Andries, M., Bianchi, M., Huynh, K. K., & Pouget, S. (2025). Return predictability, expectations, and investment: Experimental evidence. *Review of Financial Studies*, *38*(6), 1687–1729.

Arrow, K. J. (1962). The economic implications of learning by doing. *Review of Economic Studies*, *29*(3), 155–173.

Barber, B. M., Huang, X., & Odean, T. (2016). Which factors matter to investors? evidence from mutual fund flows. *Review of Financial Studies*, *29*(10), 2600–2642.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In *Handbook of the Economics of Finance* (pp. 1053–1128). Elsevier.

Bastianello, F., Décaire, P., & Guenzel, M. (2024). Mental models and financial forecasts. *Available at SSRN*, *5004839*.

Ben-David, I., Li, J., Rossi, A., & Song, Y. (2022). What do mutual fund investors really care about? *Review of Financial Studies*, *35*(4), 1723–1774.

Bennett, J. A., Sias, R. W., & Starks, L. T. (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies*, *16*(4), 1203–1238.

Best, M. J., & Grauer, R. R. (1991). On the sensitivity of mean-variance-efficient portfolios to changes in asset means: Some analytical and computational results. *Review of Financial Studies*, *4*(2), 315–342.

Bickel, P. J., Ritov, Y., & Tsybakov, A. B. (2009). Simultaneous analysis of lasso and dantzig selector. *Annals of Statistics*, 1705–1732.

Blankespoor, E., deHaan, E., & Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*, *70*(2-3), 101344.

Bonelli, M., & Foucault, T. (2023). Displaced by big data: Evidence from active fund managers. *Available at SSRN*, *4527672*.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Cao, H. H., Han, B., Hirshleifer, D., & Zhang, H. H. (2011). Fear of the unknown: Familiarity and economic decisions. *Review of Finance*, *15*(1), 173–206.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82.

Chan, L. K., Chen, H.-L., & Lakonishok, J. (2002). On mutual fund investment styles. *Review of Financial Studies*, *15*(5), 1407–1437.

Chen, A. Y., & Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, *11*(02), 207–264.

Chen, H., Hwang, B.-H., & Peng, Z. (2025). Why do investors like short-leg securities? Evidence from a textual analysis of buy recommendations. *Review of Financial Studies*, *38*(12), 3729–3767.

Chen, S., Sialm, C., & Xu, D. X. (2025). The growth and performance of artificial intelligence in asset management. *Available at SSRN*, *5638612*.

Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2009). Reinforcement learning and savings behavior. *Journal of Finance*, *64*(6), 2515–2534.

Cici, G., Gehde-Trapp, M., Göricke, M.-A., & Kempf, A. (2018). The investment value of fund managers' experience outside the financial sector. *Review of Financial Studies*, *31*(10), 3821–3853.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance*, *66*(4), 1047–1108.

Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance*, *63*(4), 1977–2011.

Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *Journal of Finance*, *75*(1), 173–228.

Del Guercio, D. (1996). The distorting effect of the prudent-man laws on institutional equity investments. *Journal of Financial Economics*, *40*(1), 31–62.

DellaVigna, S., & Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *Journal of Finance*, *64*(2), 709–749.

Edelen, R. M., Ince, O. S., & Kadlec, G. B. (2016). Institutional investors and stock return anomalies. *Journal of Financial Economics*, *119*(3), 472–488.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, *49*(3), 283–306.

Fleiss, S., Kominers, S. D., & Ughetta, C. B. (2017). Quantopian: A new model for active management. *HBS Case Study 9-218-046*.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *Quarterly Journal of Economics*, *129*(4), 1661–1710.

Goetzmann, W. N., Ingersoll, J. E., Spiegel, M., & Welch, I. (2002). Sharpening Sharpe ratios.

Greene, W. H. (1981). Sample selection bias as a specification error: A comment. *Econometrica*, 795–798.

Greenwood, R., & Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics*, *93*(2), 239–258.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, *85*(5), 1088–1105.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, *70*(3), 393–408.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *Review of Financial Studies*, *33*(5), 2223–2273.

Hanna, R., Mullainathan, S., & Schwartzstein, J. (2014). Learning through noticing: Theory and evidence from a field experiment. *Quarterly Journal of Economics*, *129*(3), 1311–1353.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). . . . and the cross-section of expected returns. *Review of Financial Studies*, *29*(1), 5–68.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of economic and social measurement* (pp. 475–492). NBER.

Hellwig, M. F. (1980). On the aggregation of information in competitive markets. *Journal of Economic Theory*, *22*(3), 477–498.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, *33*(5), 2019–2133.

Huberman, G. (2001). Familiarity breeds investment. *Review of Financial Studies*, *14*(3), 659–680.

Jensen, T. I., Kelly, B., & Pedersen, L. H. (2023). Is there a replication crisis in finance? *Journal of Finance*, *78*(5), 2465–2518.

Kacperczyk, M., & Seru, A. (2007). Fund manager use of public information: New evidence on managerial skills. *Journal of Finance*, *62*(2), 485–528.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, *84*(2), 571–626.

Kempf, E., Manconi, A., & Spalt, O. G. (2017). Learning by doing: The value of experience and the origins of skill for mutual fund managers. *Available at SSRN*, *2124896*.

Kleinberg, J., Ludwig, J., Mullainathan, S., & Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review*, *105*(5), 491–495.

Knight, K., & Fu, W. (2000). Asymptotics for lasso-type estimators. *Annals of Statistics*, 1356–1378.

Lettau, M., Ludvigson, S. C., & Manoel, P. (2018). Characteristics of mutual fund portfolios: Where are the value funds? *NBER Working Paper*, *25381*.

Lewellen, J. (2011). Institutional investors and the limits of arbitrage. *Journal of Financial Economics*, *102*(1), 62–80.

Linnainmaa, J. T. (2011). Why do (some) households trade so much? *Review of Financial Studies*, *24*(5), 1630–1666.

Linnainmaa, J. T., & Roberts, M. R. (2018). The history of the cross-section of stock returns. *The Review of Financial Studies*, *31*(7), 2606–2649.

List, J. A. (2003). Does market experience eliminate market anomalies? *Quarterly Journal of Economics*, *118*(1), 41–71.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, *30*.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*(1), 77–91.

Martin, I. W., & Nagel, S. (2022). Market efficiency in the age of big data. *Journal of Financial Economics*, *145*(1), 154–177.

Matějka, F., & McKay, A. (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review*, *105*(1), 272–298.

McLean, D. R., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, *71*(1), 5–32.

McLean, D. R., Pontiff, J., & Reilly, C. (2025). Taking sides on return predictability. *Journal of Financial Economics*, *173*, 104158.

Montiel Olea, J. L., Ortoleva, P., Pai, M. M., & Prat, A. (2022). Competing models. *Quarterly Journal of Economics*, *137*(4), 2419–2457.

Nicolosi, G., Peng, L., & Zhu, N. (2009). Do individual investors learn from their trading experience? *Journal of Financial Markets*, *12*(2), 317–336.

Oprea, R. (2020). What makes a rule complex? *American Economic Review*, *110*(12), 3913–3951.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Puri, I. (2025). Simplicity and risk. *Journal of Finance*, *80*(2), 1029–1080.

Schwarz, C. G., & Potter, M. E. (2016). Revisiting mutual fund portfolio disclosure. *Review of Financial Studies*, *29*(12), 3519–3544.

Seasholes, M. S., & Zhu, N. (2010). Individual investors and local bias. *Journal of Finance*, *65*(5), 1987–2010.

Seru, A., Shumway, T., & Stoffman, N. (2010). Learning by trading. *Review of Financial Studies*, *23*(2), 705–739.

Sheng, J., Sun, Z., Yang, B., & Zhang, A. L. (forthcoming). Generative AI and asset management. *Review of Financial Studies*.

Tibshirani, R. J. (2013). The lasso problem and uniqueness. *Electronic Journal of Statistics*, *7*, 1456–1490.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), 207–232.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, *185*(4157), 1124–1131.

Zheng, Y. (2017). Quants in Utopia? Quantopian and its crowd-wisdom hedge-fund model. *HKU Case Study HK1109*.

Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, *101*(476), 1418–1429.

Appendix

Figures

Figure 1: Trading Contest Backtest vs. Live periods. Stylized illustration of how the Backtest period expands with each new contest, whereas the (disjoint) Live period rolls forward from one contest to the next.

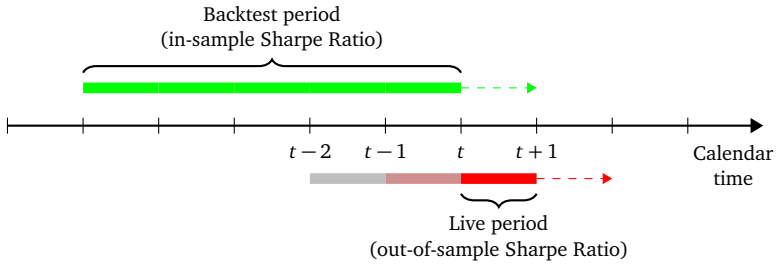


Figure 2: Distinction Between Macro Signal Release Days and Macro Signal Availability. Contestants take part in one or more trading contests t by entering trading strategies that run over an extended calendar period. The historical periods of all contests overlap in calendar time, so each historical calendar day τ can be matched to multiple trading strategies entered into various contests t: this allows entries to be compared for the same days τ. The values of macro indicators are updated by the Quantiacs trading platform on a subset of these calendar days (highlighted in solid colors) but only accessible to trading strategies entered into later contests (highlighted in red).

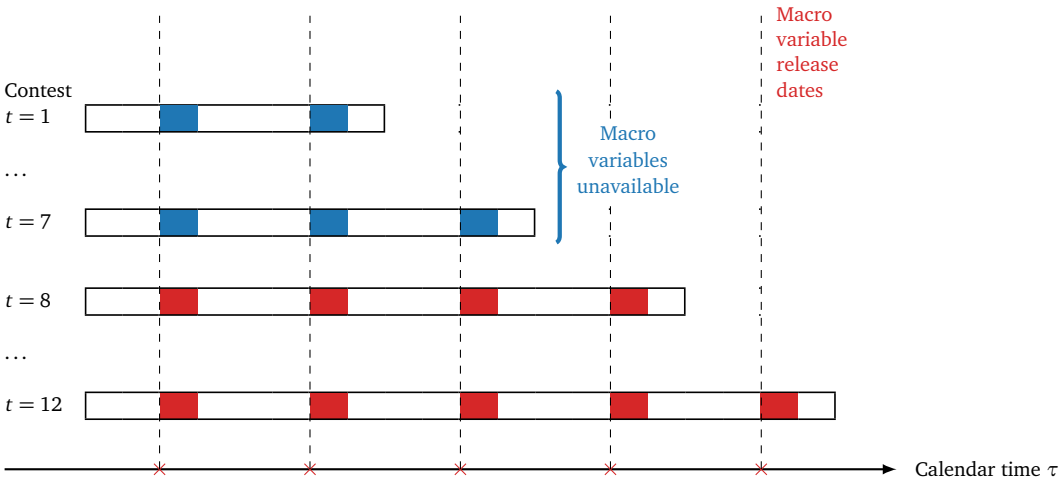


Figure 3: Variation in the Number of Signals Released on Macro Release Dates. This chart counts the number of macro variables that were released to trading strategies on the Quantiacs platform, including both in-sample/Backtest and out-of-sample/Live periods. Variables were released in monthly batches, but not every variable was made available or updated by the platform. The historical calendar dates on which one or more macro variables were updated are termed "macro release days."

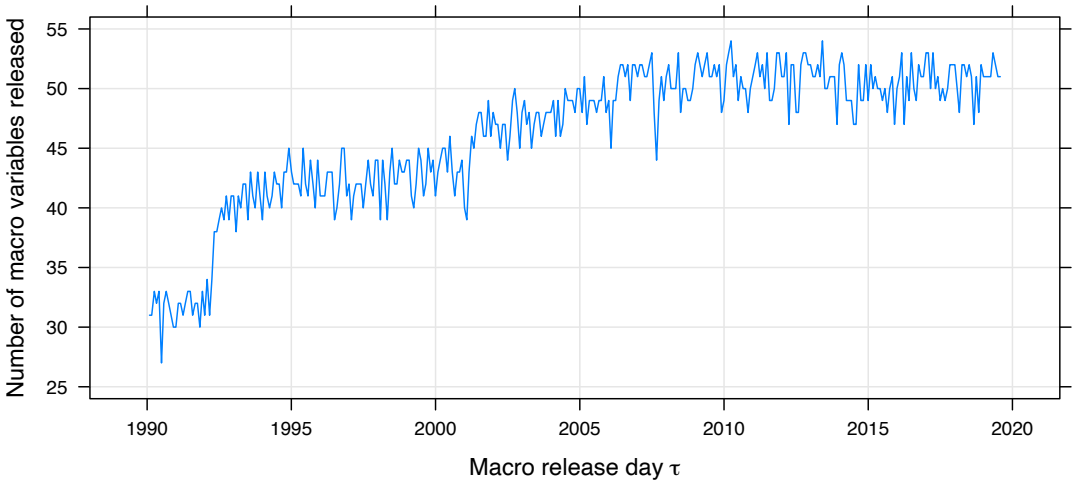
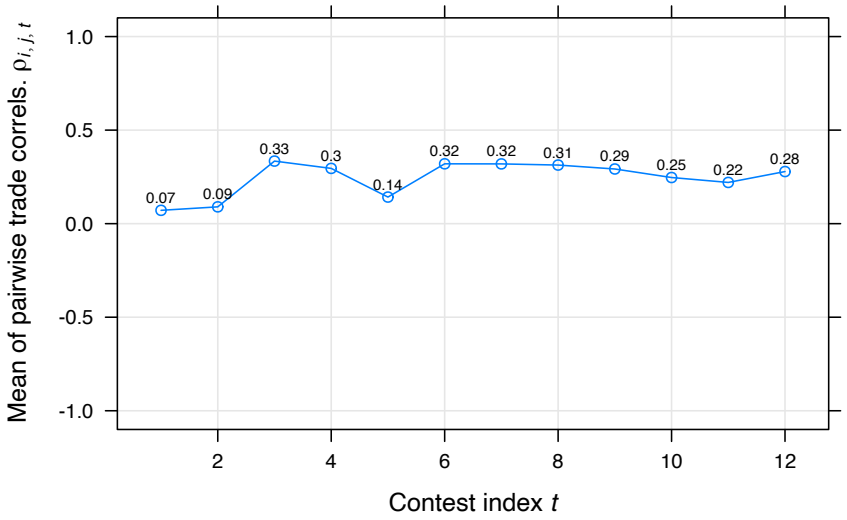


Figure 4: Cross-Sectional Mean Correlation in Trading. For each trading contest index t, this chart displays the cross-sectional mean of the pairwise correlations $\rho_{i,j,t}$ in daily trading strategy turnovers in the contest. Self-correlations are excluded.



Tables

Table 1: Trading Contest Leaderboards. Summaries of each of the 12 contests in the leaderboard sample. "OOS" denotes out-of-sample, "IQR" denotes the interquartile range, and "SD" denotes the cross-sectional standard deviation. The Entries columns summarize the number of entries submitted per contestant.

					Backtest/In-Sample Sharpe Ratios					Live/OOS Sharpe Ratios							
			Entries		Percentile			Dispersion		Percentile					Dispersion		Macro
Contest	Live/OOS Period	Contestants	Median	Mean	25	50	75	IQR	SD	10	25	50	75	90	IQR	SD	Signals
1	2014-12-01 – 2015-01-31	13	1	1.31	0.72	0.94	1.03	0.31	0.49	-3.85	-2.33	0.00	0.44	1.95	2.77	2.99	
2	2015-07-01 – 2015-09-30	16	2	3.62	0.38	0.59	1.38	1.00	0.83	-2.41	-2.07	-1.18	0.74	3.03	2.81	2.12	
3	2015-10-01 – 2015-12-31	23	1	1.17	0.09	0.39	0.46	0.37	1.24	-1.97	-0.63	0.26	0.98	1.63	1.61	1.55	
4	2016-01-01 – 2016-03-31	30	1	3.53	0.15	0.86	2.38	2.22	2.22	-1.66	-1.20	0.09	1.70	3.11	2.90	2.18	
5	2016-04-01 – 2016-06-30	38	2	4.05	0.43	0.76	1.92	1.49	1.41	-2.72	-1.49	-0.21	1.16	2.50	2.65	2.46	
6	2016-08-01 – 2016-10-31	87	1	3.02	0.33	0.64	2.24	1.91	1.62	-2.95	-2.13	-0.75	-0.22	0.75	1.91	1.57	
7	2017-01-01 – 2017-03-31	125	1	2.54	0.25	0.39	1.53	1.28	1.79	-2.45	-1.38	-1.03	0.67	1.44	2.05	1.69	
8	2017-04-15 – 2017-07-31	92	1	3.50	0.38	1.19	2.36	1.98	2.63	-1.46	-0.48	0.68	1.41	1.93	1.89	1.67	✓
9	2017-10-01 – 2018-01-31	163	1	2.31	0.30	0.38	1.90	1.60	5.57	-2.07	-0.35	1.00	2.07	2.90	2.42	2.04	✓
10	2018-02-01 – 2018-05-31	63	1	3.73	0.40	1.61	4.92	4.52	4.19	-2.67	-1.50	-0.24	0.23	1.56	1.73	2.09	✓
11	2018-07-01 – 2018-10-31	95	1	2.88	0.38	0.69	2.50	2.12	5.12	-2.16	-1.65	-0.89	-0.58	0.42	1.06	1.46	✓
12	2019-01-01 – 2019-04-30	129	1	3.13	0.36	0.55	2.27	1.91	3.27	-2.90	-2.56	-1.21	1.65	3.43	4.21	2.61	✓
		Overall:	1	2.92													

Table 2: Trading Contest Performance Outcomes Increase with Accumulated Experience, In- and Out-of-Sample. This table shows regressions of in-sample (Backtest) & out-of-sample (Live) Sharpe Ratios (SRs) against experience.

Dependent Variables:	Backtest $SR_{i,t}$			Live $SR_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Contests Experienced$_{i,t}$	0.7091***	0.7057***	0.9721**	0.4455**	0.4666**	1.261***
	(0.2034)	(0.2007)	(0.3586)	(0.1902)	(0.1752)	(0.2750)
Intercept	✓			✓		
Contest FEs		✓	✓		✓	✓
Contestant FEs			✓			✓
N	874	874	874	874	874	874
R^2	18.42	18.97	74.42	3.50	19.27	83.42

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

Table 3: Model Agreement Increases Among Experienced Contestants. This table shows regressions for pairwise correlations of trading strategy daily turnover series indexed by i, j that have been matched by experience and by trading contest index t.

Dependent Variable:	$\rho_{i,j,t}$		
	(1)	(2)	(3)
Contests Experienced$_{i,j,t}$	0.0625***	0.0640***	0.0929*
	(0.0176)	(0.0182)	(0.0436)
(Intercept)	0.3087***		
	(0.0207)		
Contest FEs		✓	✓
Contestant i FEs			✓
N	25,829	25,829	25,829
R^2	0.11	0.94	30.49

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table 4: Trading Strategy Responses to Released Macro Signal Informativeness. Column 3 shows the result of regressing the standardized daily turnover of trading strategies on macro signal release days against the SHAP measure of release days' predictive information content, with an interaction with an indicator for investor experience. The other columns show simplifications of the main specification.

Dependent Variable:	$\text{Volume}_{i,\tau}$		
	(1)	(2)	(3)
$\text{Experienced}_{i,t}$	0.0673**		-0.3229*
	(0.0184)		(0.1208)
$\text{Informativeness}_{\tau}$		0.6774**	0.6348*
		(0.2132)	(0.2362)
$\text{Experienced}_{i,t} \times \text{Informativeness}_{\tau}$			1.025**
			(0.2357)
Intercept	✓		
Model Year FEs		✓	✓
N	142,332	142,332	142,332
R^2	0.01	0.03	0.05

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table 5: Trading Strategy Responses to Released Macro Signal Familiarity. Columns 3 and 5 show the result of regressing the standardized daily turnover of trading strategies on macro release days against two indices of macro release day familiarity, with an indicator for investor experience. The other columns show simplifications of the main specifications. Familiarity measures are based on news article mentions in columns 2–3, and book mentions in columns 4–5.

Dependent Variable:	$\text{Volume}_{i,\tau}$				
Familiarity Index:		News Articles		Books	
	(1)	(2)	(3)	(4)	(5)
$\text{Experienced}_{i,t}$	0.0673**		-0.3381		-0.1500
	(0.0184)		(0.3085)		(0.2425)
$\text{Familiarity}_{\tau}$		0.0027***	0.0026***	0.0026***	0.0026***
		(0.0003)	(0.0003)	(0.0005)	(0.0005)
$\text{Experienced}_{i,t} \times \text{Familiarity}_{\tau}$			0.0043		0.0023
			(0.0031)		(0.0024)
Intercept	✓				
Benchmark Year FEs		✓	✓	✓	✓
N	142,332	142,332	142,332	142,332	142,332
R^2	0.01	0.02	0.03	0.01	0.03

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

Table 6: Trading Strategy Responses to Both Macro Signal Informativeness and Familiarity. Standardized daily turnover of trading strategies on macro release days, regressed against the index of macro release day informativeness, as well as one of two indices of macro release day familiarity. The familiarity and informativeness indices are interacted with an indicator for investor experience. Familiarity measures are based on news article mentions in columns (1) and (2), and book mentions in columns (3) and (4), respectively.

Dependent Variable:	$\text{Volume}_{i,\tau}$			
Familiarity Index:	News Articles		Books	
	(1)	(2)	(3)	(4)
$\text{Familiarity}_{\tau}$	0.0016**	0.0016**	0.0017**	0.0017**
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
$\text{Informativeness}_{\tau}$	0.5714*	0.5282*	0.6089**	0.5646*
	(0.2219)	(0.2462)	(0.2137)	(0.2378)
$\text{Experienced}_{i,t}$	-0.3047	-0.4709	-0.1192	-0.3483
	(0.3103)	(0.3715)	(0.2448)	(0.3374)
$\text{Experienced}_{i,t} \times \text{Familiarity}_{\tau}$	0.0039	0.0016	0.0019	0.0002
	(0.0031)	(0.0027)	(0.0024)	(0.0020)
$\text{Experienced}_{i,t} \times \text{Informativeness}_{\tau}$		1.006***		1.037***
		(0.1402)		(0.1944)
Benchmark/Model Year FEs	✓	✓	✓	✓
N	142,332	142,332	142,332	142,332
R^2	0.06	0.06	0.06	0.06

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

Table 7: Trading Strategy Performance Following Macro Signal Release Days. The dependent variable is the return earned by an investor's trading strategy following the updating of macro variables on the Quantiacs platform on day τ and up to the day before the next update of macro variables (on a future day τ'). Post-update returns are winsorized at the 1% and 99% levels. Informativeness$_\tau$ is the SHAP measure of the release day's predictive information content. The Familiarity$_\tau$ measures are based on news article mentions (column 3) or book mentions (column 4).

Dependent Variable:	Post-Update Return$_{i,\tau\to\tau}$ (%)			
	(1)	(2)	(3)	(4)
Informativeness$_\tau$	0.6465	0.6133	1.463*	1.563**
	(0.3451)	(0.3530)	(0.5274)	(0.4589)
Experienced$_{i,t}$	-1.355	-1.794*	-1.730	-1.724*
	(0.9475)	(0.8358)	(0.8123)	(0.8081)
Informativeness$_\tau$ × Experienced$_{i,t}$	6.907*	4.023**	3.853**	3.837**
	(3.075)	(1.014)	(0.9770)	(0.9640)
Familiarity$_\tau$			-0.0048*	-0.0057**
			(0.0019)	(0.0017)
Familiarity Index			News Articles	Books
Model & Benchmark Year FEs	✓	✓	✓	✓
Contestant FEs		✓	✓	✓
N	156,691	156,691	156,691	156,691
R^2	0.82	4.21	4.24	4.25

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

Table 8: Experience Gradient in the Gains from the Availability of Additional Predictive Signals. This table shows regressions of investors' out-of-sample performance against macro data availability interacted with experience. The dependent variable is the excess live Sharpe Ratio over the Sharpe Ratio of the benchmark index during the same period, which controls for time variation. The indicator "Macro Signals Available$_t$" equals one for Treatment observations and zero for Control observations, as defined in Section 5.2.

Panel A: Linear Relationship

	Dependent variable:		
	Excess Live $SR_{i,t}$		
	(1)	(2)	(3)
(Intercept)	-2.181^{***}	-1.959^{***}	-1.470^{**}
	(0.566)	(0.525)	(0.626)
Contests Experienced$_{i,t}$	1.030^{***}	1.003^{***}	0.589^{***}
	(0.263)	(0.240)	(0.186)
Macro Signals Available$_t$		−0.318	−1.352
		(0.609)	(1.069)
Contests Experienced$_{i,t}$ × Macro Signals Available$_t$			0.908^{**}
			(0.439)
N	830	830	830
R^2	4.8	5.3	6.3

Panel B: Indicator Variables

	Dependent variable:		
	Excess Live $SR_{i,t}$		
	(1)	(2)	(3)
(Intercept)	-1.162^{***}	-0.970^{**}	-0.899^{**}
	(0.341)	(0.425)	(0.451)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	1.332^{***}	1.293^{***}	1.044^{***}
	(0.266)	(0.257)	(0.271)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	1.673^{*}	1.654^{*}	−0.004
	(0.914)	(0.896)	(0.459)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	3.021^{***}	2.918^{***}	2.245^{***}
	(0.433)	(0.421)	(0.507)
Macro Signals Available$_t$		−0.311	−0.428
		(0.614)	(0.659)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$ × Macro Signals Available$_t$			0.478
			(0.504)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$ × Macro Signals Available$_t$			2.973^{**}
			(1.491)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$ × Macro Signals Available$_t$			2.221^{***}
			(0.527)
N	830	830	830
R^2	5.0	5.5	6.7

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table 9: Selection Effects Do Not Explain the Experience Gradient: Heckman Two-Stage Estimates. This table shows the results of Heckman (1976) (i.e. Type II Tobit) two-stage selection models for implementing selection bias corrections to the regression of out-of-sample performance against experience. The first stage models the probability of participation, while the second stage models the outcome of interest.

		All contests	*Contests 1-7*	*Contests 8-12*
Stage		Live $SR_{i,t}$	Live $SR_{i,t}$	Live $SR_{i,t}$
1. *Selection*	(Intercept)	1.95^{***}	2.38^{***}	1.50^{***}
		(0.18)	(0.29)	(0.34)
	Contests Experienced$_{i,t}$	-0.88^{***}	-1.22^{***}	-0.77^{***}
		(0.05)	(0.10)	(0.05)
	Quantopian Search Index$_t$	-0.01^{**}	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
	Ratio of Entries to Contest Mean$_{i,t-1}$	0.23^{***}	0.24^{***}	0.22^{***}
		(0.04)	(0.08)	(0.04)
2. *Outcome*	(Intercept)	-0.42^{***}	-0.79^{**}	-0.04
		(0.13)	(0.32)	(0.17)
	Contests Experienced$_{i,t}$	0.84^{***}	0.55	0.86^{***}
		(0.17)	(0.39)	(0.20)
	Inverse Mills Ratio	-0.83^{***}	0.33	-1.27^{***}
		(0.32)	(0.54)	(0.41)
	σ	2.13	1.89	2.31
	ρ	-0.39	0.17	-0.55
	R^2	4	7	4
	Num. obs.	1482	482	1000
	Censored	621	163	458
	Observed	861	319	542

Standard errors (in parentheses) computed according to Greene (1981). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 10: Experience Gradient in Adoption Penalties and the Extensive Margin of Signal Adoption. This table shows regressions in which the depedent variables are the results of estimating individual-specific subjective penalties $\lambda_{i,t}$ and the count of macroeconomic indicators adopted based on the individual investor-specific model presented in Section 6.1; details of the estimation procedure are described in Section 6.2. The independent variable is the investor's experience, taking part in the sample of contests where macro signals were available.

Dependent Variables:	$\log(\widehat{\lambda}_{i,t})$	Macro variables selected$_{i,t}$
	(1)	(2)
Experience$_{i,t}$	-0.1836***	0.3099**
	(0.0395)	(0.1574)
Contest FEs	✓	✓
Regression	OLS	Poisson
N	425	425
R^2	10.9	12.7

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table 11: Aggregate Mutual Fund Portfolio Tilts and Relation to Out-of-Sample Fund Alpha. This table shows that aggregate portfolio tilts predict funds' next-period α. The independent variable $\overline{\text{Portfolio Tilt}}_{p,t}$ (Eqn. (39)) is the aggregated tilt of a portfolio p in the direction of return predictability at the end of year-quarter t, for publicly available signals only. The dependent variables consist of monthly means (%) of the portfolio's CAPM α over the 12-month period following t. The α calculations are based on gross-of-expense-ratio portfolio returns in column 1 , and on net-of-expense-ratio portfolio returns in column 2. The sample consists of active mutual funds for which a sole manager could be identified.

Dependent Variables:	Gross CAPM $\alpha_{p,t}$	Net CAPM $\alpha_{p,t}$
	(1)	(2)
$\overline{\text{Portfolio Tilt}}_{p,t}$	0.5883**	0.5884**
	(0.2486)	(0.2486)
Portfolio FEs	✓	✓
Quarter FEs	✓	✓
N	22,049	22,118
R^2	30.56	30.83

Note: std. errs. (in paren.) are clustered by portfolio & quarter. *p<0.1; **p<0.05; ***p<0.01

Table 12: Experience Effects Within Mutual Fund Managers. This table shows the results of regressing portfolio–signal tilts (Eqn. (38)) on out-of-sample signal informativeness and its interaction with an indicator for whether the fund manager has above-median total experience in the mutual fund industry. *Fund & Portfolio Controls* (not shown) are for (log) fund size, (log) fund age, expense ratio, and portfolio turnover. The sample consists of active mutual funds for which a sole manager could be identified.

Dependent Variable:	Portfolio Signal Tilt$_{p,c,t}$			
	(1)	(2)	(3)	(4)
Signal Informativeness$_{c,\,t+1\,\text{onwards}}$	-0.1480***	-0.1733***	-0.1735***	-0.1755***
	(0.0149)	(0.0164)	(0.0164)	(0.0164)
Experienced Manager$_{p,t}$	0.0221**	0.0097	-0.0111	-0.0324***
	(0.0085)	(0.0089)	(0.0087)	(0.0093)
Experienced Manager$_{p,t}$		0.0434**	0.0432**	0.0418**
× Signal Informativeness$_{c,\,t+1\,\text{onwards}}$		(0.0167)	(0.0167)	(0.0167)
Fund & Portfolio Controls$_{p,t}$	✓	✓	✓	✓
Manager FEs	✓	✓		
Manager × Portfolio FEs			✓	✓
Quarter FEs				✓
N	3,606,834	3,606,834	3,606,834	3,606,834
R^2	3.36	3.37	3.64	3.74

Note: std. errs. (in paren.) are clustered by portfolio and quarter. *p<0.1; **p<0.05; ***p<0.01

Internet Appendix for "Learning to Predict: Investor Experience and Bias in Signal Adoption"

A Proofs and Derivations . . . 2
A.1 An Investor's Prediction Problem (Section 6.1) . . . 2
A.2 Signal Adoption and Return Predictability in Equilibrium (Section 6.3) . . . 4
B Summary Statistics for the Active Mutual Funds Sample . . . 10
C Entering a Trading Contest . . . 12
D Additional Figures for Trading Contest Analyses . . . 16
E Futures Contracts and the Benchmark Portfolio . . . 19
E.1 Futures Contract Prices . . . 19
E.2 Benchmark Portfolio to Adjust for Market Conditions . . . 22
F Macro Signals Available in a Subset of Trading Contests . . . 23
F.1 Confirming Contestant Strategies Respond to Macro Signal Updates . . . 25
F.2 Daily Macro Signal Informativeness vs. Familiarity . . . 29
G Robustness Checks for Trading Contest Analyses . . . 30
G.1 Crash Risk . . . 30
G.2 Competitive Intensity . . . 31
G.3 Controlling for Entry Count . . . 33
G.4 Official Scores . . . 34
H Stock Characteristics Used to Construct Predictive Signals . . . 37
References in Internet Appendix . . . 55

A Proofs and Derivations

A.1 An Investor's Prediction Problem (Section 6.1)

Proposition 1. *Fix any vector of bounds* $\{\rho_j\}$ *in* (18)*, let* $\widehat{\boldsymbol{b}}$ *solve* (17)*, set* $\widehat{\kappa} \triangleq \|\boldsymbol{y} - \boldsymbol{S}\widehat{\boldsymbol{b}}\|_2$ *(its residual norm), and assume* $\widehat{\kappa} > 0$*. Then every solution of*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \tfrac{1}{2}\|\boldsymbol{y} - \boldsymbol{S}\boldsymbol{b}\|_2^2 + \sum_{j=1}^{m} \delta_j |b_j|, \qquad \delta_j \triangleq \widehat{\kappa}\,\rho_j, \tag{19}$$

solves (17)*; and, in the other direction,* $\widehat{\boldsymbol{b}}$ *itself solves* (19).

Proof. The first step is a reformulation: Xu, Caramanis, and Mannor (2010, Theorem 1) show the problem (17) is equivalent to

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \|\boldsymbol{y} - \boldsymbol{S}\boldsymbol{b}\|_2 + \sum_j \rho_j |b_j|. \tag{40}$$

The second step applies a technique similar to that of Sun and Zhang (2012). Apply the identity $a = \inf_{\kappa>0}\{a^2/(2\kappa)+\kappa/2\}$, attained at $\kappa = a$ when $a > 0$, with $a = \|\boldsymbol{y}-\boldsymbol{S}\boldsymbol{b}\|_2$: the minimization (40) equals the joint infimum of $\|\boldsymbol{y} - \boldsymbol{S}\boldsymbol{b}\|_2^2/(2\kappa) + \kappa/2 + \sum_j \rho_j |b_j|$ over $(\boldsymbol{b}, \kappa)$ with $\kappa > 0$. At fixed κ, the $\boldsymbol{b}$-problem is (19) with $\delta_j = \kappa\rho_j$ (after multiplying through by $\kappa > 0$). Because $\widehat{\kappa} = \|\boldsymbol{y} - \boldsymbol{S}\widehat{\boldsymbol{b}}\|_2 > 0$ by assumption, the joint infimum is attained at $(\widehat{\boldsymbol{b}}, \widehat{\kappa})$, which gives the second direction of the proposition; conversely, any solution $\boldsymbol{b}'$ of (19) at $\delta_j = \widehat{\kappa}\rho_j$ shares the fitted value (Tibshirani, 2013) and hence the residual norm $\widehat{\kappa}$, so $(\boldsymbol{b}', \widehat{\kappa})$ also attains the joint minimum and $\boldsymbol{b}'$ solves (40), hence (17). □

Corollary 1. *In the setting of Proposition 1, fix a solution* $\widehat{\boldsymbol{b}}$ *of* (17) *with residual norm* $\widehat{\kappa} > 0$ *and associated parameters* $\delta_j = \widehat{\kappa}\,\rho_j$*, and assume the signals are orthonormal:* $\boldsymbol{S}^T\boldsymbol{S} = \boldsymbol{I}$*. Then* $\widehat{\boldsymbol{b}}$ *is the unique solution of* (19) *and the biased investor predicts*

$$\widehat{y} = \boldsymbol{s}\,\widehat{\boldsymbol{b}}, \tag{20}$$

where $\boldsymbol{s}$ *is an m-dimensional row vector consisting of the m predictive signals and* $\widehat{\boldsymbol{b}}$ *is an m-dimensional column vector of signal loadings consisting of elements*

$$\widehat{b}_k = \operatorname{sign}(\boldsymbol{s}_k^T\boldsymbol{y}) \max\left\{|\boldsymbol{s}_k^T\boldsymbol{y}| - \delta_k, 0\right\}. \tag{21}$$

Proof. Orthonormality $\boldsymbol{S}^\top \boldsymbol{S} = \boldsymbol{I}$ makes the squared loss in (19) strictly convex in $\boldsymbol{b}$, so (19) has a unique solution; by Proposition 1, $\widehat{\boldsymbol{b}}$ solves (19) and is therefore that solution. It remains to derive its form. As the ℓ_1 norm is not differentiable, I write the (necessary and sufficient) Karush–Kuhn–Tucker optimality conditions in terms of the subdifferential ∂ (Lee, Sun, Sun, and Taylor, 2016), for the problem (19):

$$\mathbf{0} \in \boldsymbol{S}^\top(\boldsymbol{S}\widehat{\boldsymbol{b}} - \boldsymbol{y}) + \partial\big(\textstyle\sum_k \delta_k |b_k|\big),$$

which orthonormality $\boldsymbol{S}^\top \boldsymbol{S} = \boldsymbol{I}$ simplifies to

$$\mathbf{0} \in \widehat{\boldsymbol{b}} - \boldsymbol{S}^\top \boldsymbol{y} + \partial\big(\textstyle\sum_k \delta_k |b_k|\big).$$

Both terms are separable, so each coordinate stands on its own:

$$0 \;=\; \widehat{b}_k - \tilde{b}_k + \delta_k \widehat{z}_k, \qquad \widehat{z}_k = \operatorname{sign}(\widehat{b}_k) \text{ for } \widehat{b}_k \neq 0, \quad \widehat{z}_k \in [-1, 1] \text{ otherwise,}$$

with $\tilde{b}_k = \boldsymbol{s}_k^\top \boldsymbol{y}$. When $|\tilde{b}_k| > \delta_k$ the coordinate is active, $\widehat{b}_k = \tilde{b}_k - \operatorname{sign}(\tilde{b}_k)\,\delta_k$; when $|\tilde{b}_k| \leq \delta_k$, $\widehat{b}_k = 0$ solves it with $\widehat{z}_k = \tilde{b}_k / \delta_k \in [-1, 1]$ if $\delta_k > 0$, and with $\widehat{z}_k = 0$ in the remaining case $\delta_k = \tilde{b}_k = 0$. These two cases comprise Eqn. (21). □

Corollary 2 (Signal loadings vs. informativeness & bias). *Under the orthonormality of Corollary 1, let the signal loadings $\widehat{\boldsymbol{b}}$ solve* (19) *with signal-specific penalties $\delta_k > 0$, and orient each signal so that its benchmark contribution is nonnegative, $x_k \triangleq \boldsymbol{s}_k^\top \boldsymbol{y} \geq 0$ (without loss of generality), so that $\widehat{b}_k = \max\{x_k - \delta_k, 0\}$ per* (21)*. Then:*

(i) At a fixed penalty δ_k, the loading $\widehat{b}_k$ is nondecreasing in the contribution x_k, and strictly increasing wherever $\widehat{b}_k > 0$.

(ii) At a fixed contribution x_k, the loading $\widehat{b}_k$ is nonincreasing in the penalty δ_k, and strictly decreasing wherever $\widehat{b}_k > 0$.

Proof. Immediate from $\widehat{b}_k = \max\{x_k - \delta_k, 0\}$: on $\{x_k > \delta_k\}$ the loading equals $x_k - \delta_k$, increasing in x_k and decreasing in δ_k; on $\{x_k \leq \delta_k\}$ it is zero. □

A.2 Signal Adoption and Return Predictability in Equilibrium (Section 6.3)

Lemma 1 (Investors' signal loadings). *The unique solution of* (24) *is* $\theta_i^* = \max\{b - \delta_i, 0\}$.

Proof. By (23), $v - \bar{v} = bs + \varepsilon$; since $\mathbb{E}[s^2] = 1$ and $\mathbb{E}[s\varepsilon] = 0$, expanding gives $\mathbb{E}[(v - \bar{v} - \theta s)^2] = \mathbb{E}[(bs + \varepsilon - \theta s)^2] = (\theta - b)^2 + \sigma_\varepsilon^2$. Up to a constant, the objective (24) is therefore $\frac{1}{2}(\theta - b)^2 + \delta_i|\theta|$: a strictly convex scalar lasso, whose unique solution is the soft threshold $\theta_i^* = \text{sign}(b)\max\{|b| - \delta_i, 0\}$ (Friedman, Hastie, Höfling, and Tibshirani, 2007). Since $b > 0$, $\theta_i^* = \max\{b - \delta_i, 0\}$. □

Proposition 2 (Equilibrium price and expected return). *Let* $a > 0$. *Market clearing* $\int_0^1 q_i \, di = Z$ *admits a linear equilibrium* $p = p_0 + \pi \, bs - \Lambda Z$, *unique in the linear class, with constants, in order of determination,*

$$\xi = \frac{\gamma}{\tau_A \Phi}, \qquad \tau_q = \frac{1}{\xi^2 \sigma_Z^2} = \frac{\tau_A^2 \Phi^2}{\gamma^2 \sigma_Z^2}, \qquad \beta_q = \frac{\tau_q}{\tau_q + \tau_\mu}, \qquad \tau_N = \left(\sigma_\varepsilon^2 + (\tau_\mu + \tau_q)^{-1}\right)^{-1}, \tag{28}$$

$$\pi = \frac{\tau_A \Phi + (1-a)\,\tau_N \,\beta_q}{M} \in [0,1], \qquad \Lambda = \pi \, \xi, \qquad p_0 = \bar{v} + \frac{(1-a)\,\tau_N \,\beta_q \,\xi \,\bar{Z}}{M}, \tag{29}$$

where $\tau_A \triangleq 1/\sigma_\varepsilon^2$ *is an adopter's perceived payoff precision,* $\tau_\mu \triangleq 1/b^2$ *the prior precision of the signal's content* bs, τ_q *the precision of the price statistic* Ψ *about the signal's content,* τ_N *a non-adopter's posterior payoff precision, and* $M \triangleq a\,\tau_A + (1-a)\,\tau_N$ *aggregates risk-bearing capacity; and the expected return conditional on the signal is*

$$\mathbb{E}[v - p \mid s] \;=\; \frac{\gamma \bar{Z}}{M} \;+\; (1-\pi)\, bs. \tag{30}$$

Proof. Conjecture the linear form and solve for the constants (Grossman and Stiglitz, 1980; Hellwig, 1980).

Step 1: the non-adopter's inference. Observing p is, for a non-adopter, equivalent to observing the statistic $\Psi = (p - p_0)/\pi = bs - (\Lambda/\pi)Z$ of the setup (the division requires $\pi > 0$, verified in Step 6): the signal's content blurred by supply noise, a signal of precision τ_q against the prior precision τ_μ, where, as in the setup, $\xi = \Lambda/\pi$, is provisional until determined in (28). Against the prior $bs \sim \mathcal{N}(0, b^2)$ of precision τ_μ, the statistic Ψ carries the signal's content with noise $-\xi Z$ of precision $\tau_q = 1/(\xi^2 \sigma_Z^2)$, so Normal updating weighs the signal and prior by relative precision: $\mathbb{E}[bs|\Psi] = \beta_q\big(\Psi - \mathbb{E}[\Psi]\big) = \beta_q(\Psi + \xi\bar{Z})$ with $\beta_q = \tau_q/(\tau_q + \tau_\mu)$, and the posterior variance of bs is $(\tau_\mu + \tau_q)^{-1}$. Adding the payoff noise ε, the posterior payoff variance is $\sigma_\varepsilon^2 + (\tau_\mu + \tau_q)^{-1} = 1/\tau_N$, with β_q and τ_N as stated.

Step 2: demands. With the adopter's coefficient $\phi_i\, b$ from Lemma 1 and (25), the demands are $q_i = \gamma^{-1}\tau_A(\bar{v} + \phi_i\, bs - p)$ for adopter i and $q_N = \gamma^{-1}\tau_N\big(\bar{v} + \beta_q\, bs - \beta_q\xi(Z - \bar{Z}) - p\big)$ for a non-adopter.

Step 3: matching coefficients. Substitute the conjecture $p = p_0 + \pi\, bs - \Lambda Z$ into the clearing condition $\int_0^1 q_i\, di = Z$, multiply by γ, and match the coefficients of s, Z, and the constant (the right-hand side γZ carries only Z):

$$\begin{aligned} s: &\quad \tau_A b\,(\Phi - a\pi) + (1-a)\,\tau_N b\,(\beta_q - \pi) = 0, \\ Z: &\quad a\tau_A\Lambda + (1-a)\,\tau_N(\Lambda - \beta_q\xi) = \gamma, \\ \text{constant}: &\quad a\tau_A(\bar{v} - p_0) + (1-a)\,\tau_N\big(\bar{v} - p_0 + \beta_q\xi\bar{Z}\big) = 0. \end{aligned}$$

Step 4: solving the system. In the s-equation $b > 0$ cancels, giving the stated π. Collecting terms, the Z-equation reads $M\Lambda - (1-a)\,\tau_N\beta_q\,\xi = \gamma$; substituting $\xi = \Lambda/\pi$ and the s-equation in the form $(1-a)\tau_N\beta_q = \pi M - \tau_A\Phi$,

$$M\Lambda - \big(\pi M - \tau_A\Phi\big)\frac{\Lambda}{\pi} = \frac{\tau_A\Phi\,\Lambda}{\pi} = \gamma;$$

hence $\xi = \gamma/(\tau_A\Phi)$ and $\Lambda = \pi\xi$ as stated, so ξ depends on neither β_q nor π and τ_q is pinned directly by effective adoption, with no fixed point to solve. The constant equation gives $\bar{v} - p_0 = -(1-a)\tau_N\beta_q\,\xi\bar{Z}/M$, i.e. the stated p_0.

Step 5: the expected return. The return decomposes as $v - p = (\bar{v} - p_0) + (1-\pi)bs + \varepsilon + \Lambda Z$, leaving the share $1-\pi$ of the signal's content in the return. Taking $\mathbb{E}[\,\cdot \mid s\,]$ with $Z \perp s$ and $\mathbb{E}[\varepsilon \mid s] = 0$ gives $\mathbb{E}[v - p \mid s] = (\bar{v} - p_0) + \Lambda\bar{Z} + (1-\pi)\,bs$. The intercept equals the unconditional expected return: since $\mathbb{E}[s] = 0$ and $\mathbb{E}[Z] = \bar{Z}$, the conjecture gives $\mathbb{E}[p] = p_0 - \Lambda\bar{Z}$, so $\mathbb{E}[v - p] = \bar{v} - \mathbb{E}[p] = (\bar{v} - p_0) + \Lambda\bar{Z}$, which is exactly the intercept of $\mathbb{E}[v - p \mid s]$. The clearing condition determines this quantity in expectation. In the demands of Step 2, the adopter's forecast $\bar{v} + \phi_i\, bs$ has unconditional mean $\bar{v}$ since $\mathbb{E}[s] = 0$, and the non-adopter's forecast $\bar{v} + \beta_q\, bs - \beta_q\xi(Z - \bar{Z})$ has mean $\bar{v}$ as well, since also $\mathbb{E}[Z - \bar{Z}] = 0$. Hence $\mathbb{E}[q_i] = \gamma^{-1}\tau_A(\bar{v} - p_0 + \Lambda\bar{Z})$ for an adopter and $\mathbb{E}[q_N] = \gamma^{-1}\tau_N(\bar{v} - p_0 + \Lambda\bar{Z})$ for a non-adopter, and taking expectations of $\gamma\int_0^1 q_i\, di = \gamma Z$ gives

$$\big[a\,\tau_A + (1-a)\,\tau_N\big]\big(\bar{v} - p_0 + \Lambda\bar{Z}\big) = \gamma\,\bar{Z},$$

whose bracket is M. Hence $(\bar{v} - p_0) + \Lambda\bar{Z} = \gamma\bar{Z}/M$, giving (30).

Step 6: uniqueness within the linear class. $a > 0$ implies $\Phi > 0$, since $\phi_i > 0$ on the positive-

measure set $\{\delta_i < b\}$. Any linear equilibrium with $\pi \neq 0$ reproduces the inference of Step 1, and Steps 3–4 then determine $(\xi, \tau_q, \beta_q, \tau_N, \pi, \Lambda, p_0)$ recursively, with no remaining degrees of freedom; the solved loading satisfies $\pi \geq \tau_A \Phi / M > 0$ by (29), consistent with the inference step. A linear equilibrium with $\pi = 0$ does not exist: the price would then carry no signal content and non-adopters would attach no weight to it, so aggregate demand would load on s with coefficient $\tau_A \Phi\, b/\gamma > 0$ while neither the price nor the supply loads on s, and the market could not clear state by state. □

Proposition 3 (Predictability falls with effective adoption but survives full adoption).

(i) The price loading π is strictly increasing in effective adoption Φ at any fixed adoption fraction a; equivalently, the share of the signal's content left in the return, $1-\pi$ (and with it the return's predictive slope $(1-\pi)\, b$ of Proposition 2), is strictly decreasing in Φ, with $1-\pi \to 1$ as $\Phi \to 0$. Predictability is maximal when no weight trades on the signal.

(ii) At full adoption ($a = 1$, equivalently $\delta_i < b$ almost surely), the price impounds $\pi = \Phi = 1 - \mathbb{E}_i[\delta_i]/b$, and the surviving predictive slope equals the average bias: $(1-\pi)\, b = \mathbb{E}_i[\delta_i]$. Whenever $\mathbb{E}_i[\delta_i] > 0$, full adoption does not eliminate predictability.

Proof. (i) Write $\omega \triangleq (\tau_\mu + \tau_q)^{-1}$, so $1 - \beta_q = \tau_\mu\, \omega$ and, subtracting the π of (29) from one,

$$1 - \pi \;=\; \frac{\tau_A (a - \Phi) \;+\; (1-a)\, \tau_N\, \tau_\mu\, \omega}{M}.$$

Raise Φ at a fixed a: the first numerator term falls at rate τ_A; in the second, τ_q rises by (28), so ω falls and $\tau_N\, \omega = \omega/(\sigma_\varepsilon^2 + \omega)$ falls with it; and the denominator $M = a\tau_A + (1-a)\tau_N$ rises, since $\tau_N = (\sigma_\varepsilon^2 + \omega)^{-1}$ rises as ω falls. A strictly falling numerator over a weakly rising denominator makes $1 - \pi$ strictly decreasing, hence π strictly increasing, in Φ; and since the numerator falls at rate at least τ_A while the denominator rises, $d\pi/d\Phi \geq \tau_A/M > 0$. As $\Phi \to 0$ the price carries no information ($\tau_q \to 0$, $\beta_q \to 0$), so $\pi \to 0$ and $1 - \pi \to 1$. (ii) At $a = 1$, $\delta_i < b$ almost surely, so $\phi_i = 1 - \delta_i/b$ for almost every investor and $\Phi = \mathbb{E}_i[\phi_i] = 1 - \mathbb{E}_i[\delta_i]/b$; with $M = \tau_A$, (29) gives $\pi = \Phi$, hence $(1-\pi)\, b = \mathbb{E}_i[\delta_i]$. □

Proving Proposition 4 requires two lemmas sharing a common assumption, as well as a second assumption.

Assumption 1 (Structure of investor biases). *Investor biases factor as $\delta_i = c\, \nu_i$, where the constant $c > 0$ is a common magnitude, and the draws $\nu_i \sim G$ are from a distribution on $[0, \infty)$*

with unit mean (a normalization) and are independent of b and c. Write $T \triangleq b/c$ for the adoption threshold; G is continuous at T and, where it exists, g denotes its density.

Lemma 2 (Adoption rises with informativeness, falls with the bias). *Under Assumption 1:*

(i) Adoption fraction $a = G(T)$ is nondecreasing in b and nonincreasing in c; if G has a density g positive in a neighborhood of T, both monotonicities are strict, with $da/dc = -g(T)\,T/c$.
(ii) Effective adoption $\Phi = \int_0^T (1 - t/T)\,dG(t)$ is differentiable, with

$$\frac{\partial \Phi}{\partial b} = \frac{a - \Phi}{b} \;\geq\; 0, \qquad \frac{\partial \Phi}{\partial c} = -\frac{a - \Phi}{c} \;\leq\; 0,$$

both strict whenever $a > \Phi$.

Proof. (i) By Assumption 1, $\delta_i < b$ if and only if $\nu_i < T$, so $a = \mathbb{P}(\nu_i < T) = G(T)$ (equating $\mathbb{P}(\nu_i < T)$ with $G(T) = \mathbb{P}(\nu_i \leq T)$ uses $\mathbb{P}(\nu_i = T) = 0$, which is automatic wherever a density exists). Since G is nondecreasing and $T = b/c$ rises with b and falls with c, a is nondecreasing in b and nonincreasing in c. Where G has a positive density, $a = G(T)$ is differentiable and strictly monotone in T, and the chain rule with $\partial T/\partial c = -T/c$ gives $da/dc = g(T)\,\partial T/\partial c = -g(T)\,T/c$.

(ii) By (25) and Assumption 1, $\phi_i = \max\{1 - \delta_i/b,\, 0\} = \max\{1 - \nu_i/T,\, 0\}$, so $\Phi = \mathbb{E}_i[\phi_i]$ is the stated integral. Raising T changes Φ through two effects: investors at the boundary $t = T$ enter the adopter pool, and the weight $1 - t/T$ of every adopter already under the threshold (i.e., the inframarginal adopters) rises. The entrants contribute nothing, because the weight is zero at $t = T$ (the marginal adopter enters at weight zero); each adopter under the threshold contributes the derivative $\partial(1 - t/T)/\partial T = t/T^2$. Hence

$$\frac{\partial \Phi}{\partial T} \;=\; \int_0^T \frac{t}{T^2}\,dG(t) \;=\; \frac{1}{T}\Big[\int_0^T dG(t) - \int_0^T \Big(1 - \frac{t}{T}\Big) dG(t)\Big] \;=\; \frac{a - \Phi}{T},$$

and the chain rule through $T = b/c$, with $\partial T/\partial b = 1/c$ and $\partial T/\partial c = -T/c$, gives the stated $\partial \Phi/\partial b$ and $\partial \Phi/\partial c$. □

Lemma 3 (The two channels of the common bias magnitude). *Under Assumption 1, the total derivative of the loading in the common bias magnitude decomposes as*

$$\frac{d\pi}{dc} \;=\; -\frac{a - \Phi}{c}\,\frac{d\pi}{d\Phi} \;-\; \frac{g(T)\,T}{c}\,\frac{\partial \pi}{\partial a}\Big|_{\Phi}, \qquad \frac{\partial \pi}{\partial a}\Big|_{\Phi} \;=\; -\frac{\tau_N \beta_q + \pi(\tau_A - \tau_N)}{M} \;<\; 0,$$

where $d\pi/d\Phi$ is the loading's response to effective adoption at a fixed adoption fraction, and $\partial\pi/\partial a\big|_\Phi$ its response to the adoption fraction at fixed effective adoption.

Proof. The constants of (28) depend on the aggregates only through Φ, so at a fixed Φ they are constant in a. Differentiating the identity $\pi M = \tau_A\Phi + (1-a)\,\tau_N\beta_q$ of (29) implicitly in a (the product rule on the left side, with $\partial M/\partial a = \tau_A - \tau_N$),

$$\frac{\partial\pi}{\partial a}\Big|_\Phi M \;+\; \pi(\tau_A-\tau_N) \;=\; -\tau_N\beta_q \quad\Longrightarrow\quad \frac{\partial\pi}{\partial a}\Big|_\Phi \;=\; -\frac{\tau_N\beta_q + \pi(\tau_A-\tau_N)}{M} \;<\; 0,$$

negative since $\tau_N < \tau_A$ and $\beta_q, \pi \geq 0$. With c entering $\pi(a,\Phi)$ only through the aggregates, the chain rule and Lemma 2's derivatives $\partial\Phi/\partial c = -(a-\Phi)/c$ and $\partial a/\partial c = -g(T)\,T/c$ give

$$\frac{d\pi}{dc} \;=\; \frac{d\pi}{d\Phi}\,\frac{\partial\Phi}{\partial c} \;+\; \frac{\partial\pi}{\partial a}\Big|_\Phi \frac{\partial a}{\partial c} \;=\; -\frac{a-\Phi}{c}\,\frac{d\pi}{d\Phi} \;-\; \frac{g(T)\,T}{c}\,\frac{\partial\pi}{\partial a}\Big|_\Phi .$$

□

Assumption 2 (Margin dominance). *A marginal increase in the common magnitude of investor biases c erodes effective adoption Φ at least B times as fast as it erodes the adopter fraction a:*

$$-\frac{\partial\Phi}{\partial c} \;\geq\; B\Big(-\frac{\partial a}{\partial c}\Big), \tag{32}$$

$$\textit{where } B \;\triangleq\; \frac{\sigma_\varepsilon^2\,\beta_q + (\tau_\mu+\tau_q)^{-1}}{\sigma_\varepsilon^2 + (\tau_\mu+\tau_q)^{-1}} \;=\; 1 - \frac{\sigma_\varepsilon^2\tau_\mu}{\sigma_\varepsilon^2(\tau_\mu+\tau_q)+1}, \tag{33}$$

evaluated at the given (b,c). Equivalently, at the adoption threshold,

$$a - \Phi \geq B\,g(T)\,T. \tag{34}$$

Proposition 4 (Greater bias increases return predictability). *Under Assumptions 1 and 2, for fixed informativeness b, with adopters biased on average ($a > \Phi$) and G admitting a density at the threshold, the signal's equilibrium return-predictability slope $(1-\pi)\,b$ of (30) is strictly increasing in the common magnitude c of investor biases:*

$$\frac{d\big[(1-\pi)\,b\big]}{dc} > 0. \tag{35}$$

Proof. Step 1: exact characterization, and reduction to Assumption 2. By Lemma 3,

$$\frac{d\pi}{dc} = -\frac{a-\Phi}{c}\frac{d\pi}{d\Phi} - \frac{g(T)\,T}{c}\frac{\partial\pi}{\partial a}\Big|_{\Phi},$$

so, multiplying by $-c<0$, $d\pi/dc<0$ if and only if

$$(a-\Phi)\frac{d\pi}{d\Phi} > -g(T)\,T\,\frac{\partial\pi}{\partial a}\Big|_{\Phi}. \tag{41}$$

This characterizes the comparative static exactly: the slope rises with the common bias magnitude if and only if (41) holds. The remainder of the proof verifies that Assumption 2 is sufficient for (41). Two bounds control its sides:

$$\frac{d\pi}{d\Phi} \geq \frac{\tau_A}{M} \qquad \text{and} \qquad B\,\frac{\tau_A}{M} > -\frac{\partial\pi}{\partial a}\Big|_{\Phi}.$$

Under these, the left side of (41) exceeds $(a-\Phi)\,\tau_A/M$ and the right side is less than $B\,g(T)\,T\,\tau_A/M$, so it suffices that $(a-\Phi)\geq B\,g(T)\,T$, which is Assumption 2. The two bounds are established in turn.

Step 2: the first bound. $d\pi/d\Phi\geq\tau_A/M$ is established in the proof of Proposition 3.

Step 3: the second bound. Writing $\omega\triangleq(\tau_\mu+\tau_q)^{-1}$, the identities $\tau_A-\tau_N=\tau_A\tau_N\omega$ and $\beta_q=\tau_q\,\omega$, from (28), give

$$-\frac{\partial\pi}{\partial a}\Big|_{\Phi} = \frac{\tau_N\beta_q+\pi\,(\tau_A-\tau_N)}{M} = \frac{\tau_N\,(\beta_q+\pi\,\tau_A\,\omega)}{M} < \frac{\tau_N\,(\beta_q+\tau_A\,\omega)}{M} = \frac{\tau_A}{M}B,$$

where the strict inequality uses $\pi<1$ and $\omega>0$, and the final equality is $\tau_N(\beta_q+\tau_A\omega)=\tau_A(\sigma_\varepsilon^2\beta_q+\omega)/(\sigma_\varepsilon^2+\omega)$ (substitute $\tau_N=(\sigma_\varepsilon^2+\omega)^{-1}$ and $\beta_q+\tau_A\omega=\tau_A(\sigma_\varepsilon^2\beta_q+\omega)$, using $\tau_A=1/\sigma_\varepsilon^2$). That $\pi<1$ follows from $a>\Phi$: $\pi=1$ in (29) would require $\tau_A(\Phi-a)=(1-a)\,\tau_N(1-\beta_q)$, impossible with the left side negative and the right side nonnegative.

Step 4: combining. By Lemma 2, $-\partial\Phi/\partial c=(a-\Phi)/c$ and $-\partial a/\partial c=g(T)\,T/c$, so Assumption 2 states $a-\Phi\geq B\,g(T)\,T$. If $g(T)>0$, then

$$(a-\Phi)\frac{d\pi}{d\Phi} \geq (a-\Phi)\frac{\tau_A}{M} \geq B\,g(T)\,T\,\frac{\tau_A}{M} > -g(T)\,T\,\frac{\partial\pi}{\partial a}\Big|_{\Phi},$$

which is (41); if $g(T)=0$, the right side of (41) vanishes while $a>\Phi$ makes the left side positive. Hence $d\pi/dc<0$, and at fixed $b>0$, $d\big[(1-\pi)\,b\big]/dc=-b\,d\pi/dc>0$. □

B Summary Statistics for the Active Mutual Funds Sample

Table IA.1: Mutual Fund Portfolios, Aggregate Signal Tilts, and Signal-Specific Tilts. Aggregate portfolio tilts are computed according to Eqn. (39) and signal-specific portfolio tilts are computed according to Eqn. (38). Tilts are available from 2008–2023 and use signals that are publicly available at the time. Additional data details are described in Section 7.1.

	N	Mean	Std. Dev.	10th Pctl.	Median	90th Pctl.
Portfolio–Quarter Level:						
Aggregate $\overline{\text{Portfolio Tilt}}$	144,312	−0.002	0.22	−0.26	0.002	0.25
Manager Experience (Months)	31,293	158.98	94.80	50	143	284
Portfolio Long Exposure (%)	144,312	99.29	6.04	100	100	100
Portfolio Short Exposure (%)	144,312	−0.71	6.04	0	0	0
Fund TNA ($M)	144,312	1,377.10	3,692.97	33.20	318.90	3,148.49
Fund Age (Months)	144,312	214.26	155.35	53	191	374
Expense Ratio (%)	107,996	1.08	0.38	0.67	1.04	1.52
Portfolio Turnover (%)	107,671	72.51	84.01	15	50	141
Gross CAPM α (% monthly, out-of-sample)	83,861	−0.14	0.91	−1.05	−0.09	0.73
Net CAPM α (% monthly, out-of-sample)	109,337	−0.22	0.89	−1.13	−0.17	0.63
Portfolio–Quarter–Signal Level:						
Portfolio–Signal Tilt	16,912,149	0.002	1.02	−1.13	0.004	1.07
Signal Out-of-Sample Mean Return (% monthly)	16,912,149	0.28	0.68	−0.38	0.23	1.08

Figure IA.1: Stock Return Predictors' Out-of-Sample Mean Returns. This figure plots the distribution, across the set of Chen and Zimmermann (2022) predictors, of each predictor's out-of-sample mean return based on long–short portfolio sorts. Positive values indicate predictors whose post-publication sorts earn positive average returns. The dashed gray line indicates the sample mean.

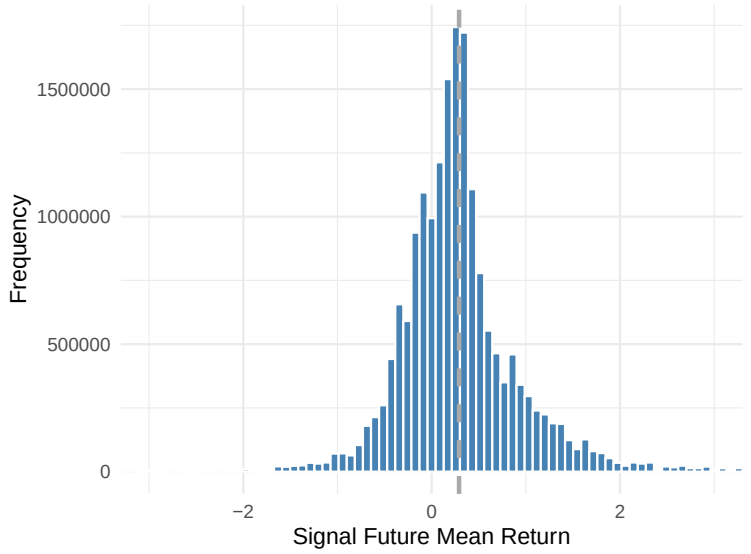
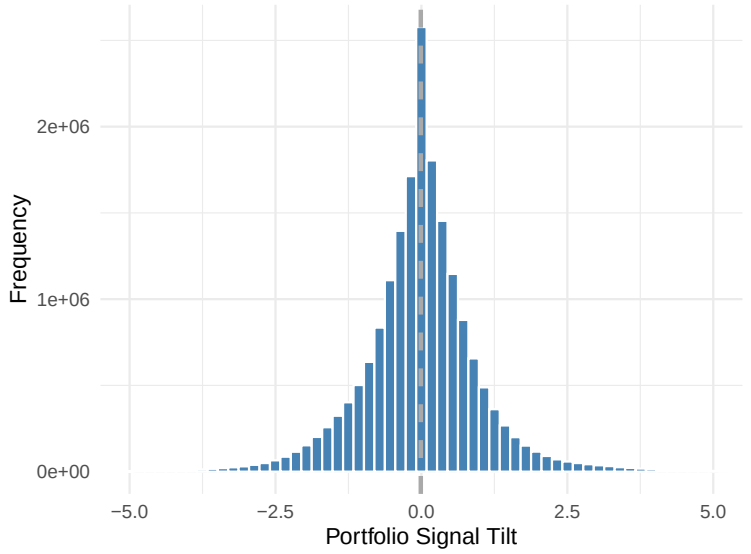


Figure IA.2: Portfolio–Signal Tilts. This figure plots the distribution of quarterly portfolio–signal tilts across mutual funds and predictors. Tilts are defined by Eqn. (38); positive tilts indicate active loadings toward stocks with higher predicted returns. The dashed gray line indicates the sample mean.



C Entering a Trading Contest

To make the trading contests setting more concrete, this appendix reviews the steps necessary to participate in a contest from the point of view of an individual investor, and include screenshots to illustrate the process.

Figure IA.3 shows an example of how to write (in Python) a systematic trading strategy that simply takes equally-weighted long positions in all available futures contracts. This code is presented as a default template to the contestant by the Quantiacs web platform. More sophisticated strategies are, of course, encouraged.

After coding up such a systematic trading strategy, the systematic investor can then use the Quantiacs platform to run a backtest of the strategy using historical market data. Figure IA.4 shows the output of such a backtest, for the long-only strategy of my above example. Various performance metrics are provided, but all are calculated on historical data, and I refer to this pre-contest period as the in-sample/backtest period.

The systematic investor may then decide to officially submit this trading strategy to a contest: if so, I term this the contestant's "entry." Once a contest has begun (i.e. during the live/out-of-sample period), entries can no longer be modified, and the contestant has effectively committed to following that systematic trading strategy for the duration of the live/out-of-sample period. The distinction between the in-sample/backtest and out-of-sample/live periods for a single contest is illustrated by Figure 1 in the manuscript.

After the contest ends, the out-of-sample Sharpe Ratios are made available, the contestants are ranked, and results are displayed in a leaderboard, as in Figure IA.5.

Figure IA.3: Implementing a Trading Strategy. Example of writing code (in Python) while logged into the trading platform in order to define a systematic trading strategy, ahead of possible entry into a trading contest. This code is presented as a default template to the contestant by the Quantiacs web platform. Lines 17-18 define a simple long-only equally-weighted portfolio, with no use of market data or macroeconomic variables. Note that uncommenting line 6 loads the `scikit-learn` (Pedregosa et al., 2011) machine learning software package.

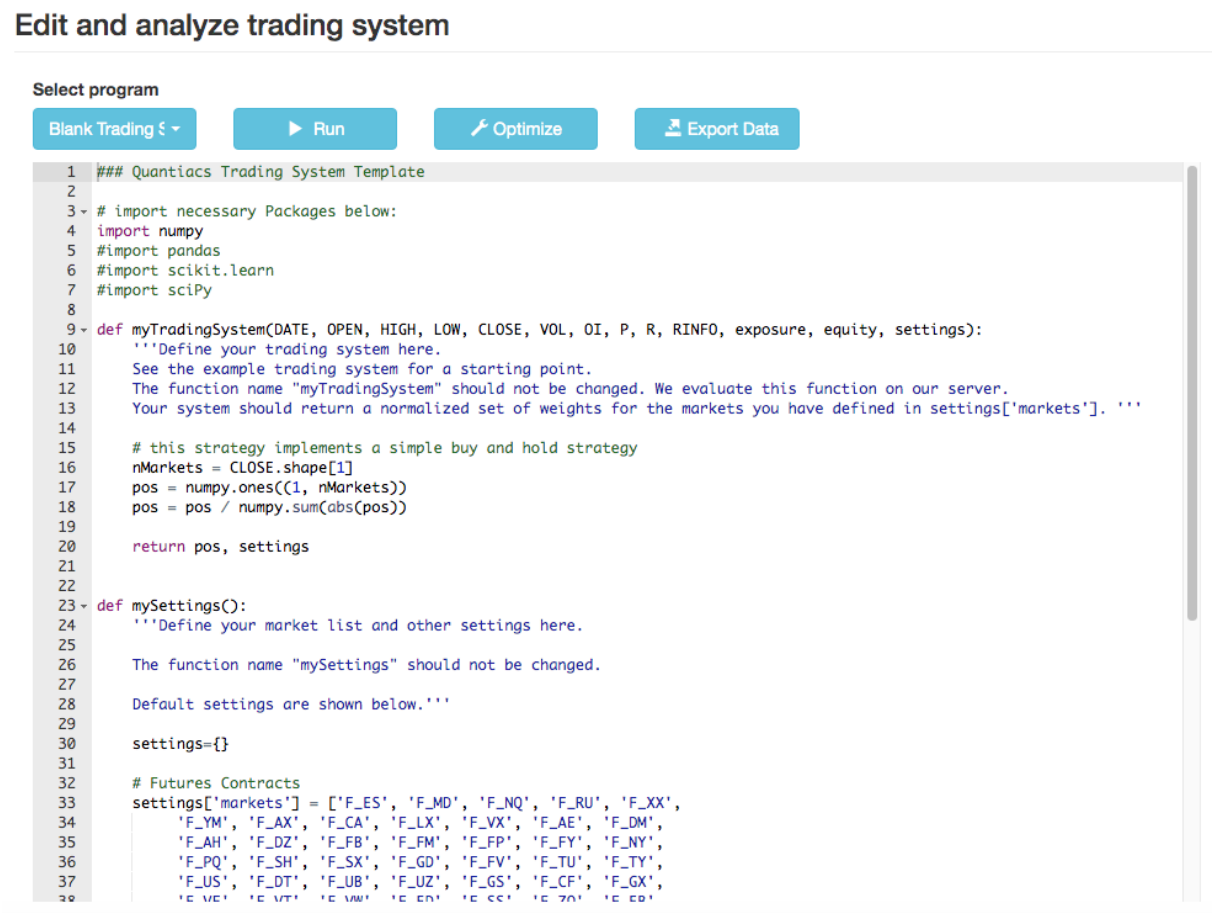


Figure IA.4: Backtesting Prior to Contest Entry. Example of in-sample backtest results for a systematic trading strategy, before an entry is submitted. At this point, a trading contest has not (yet) begun.

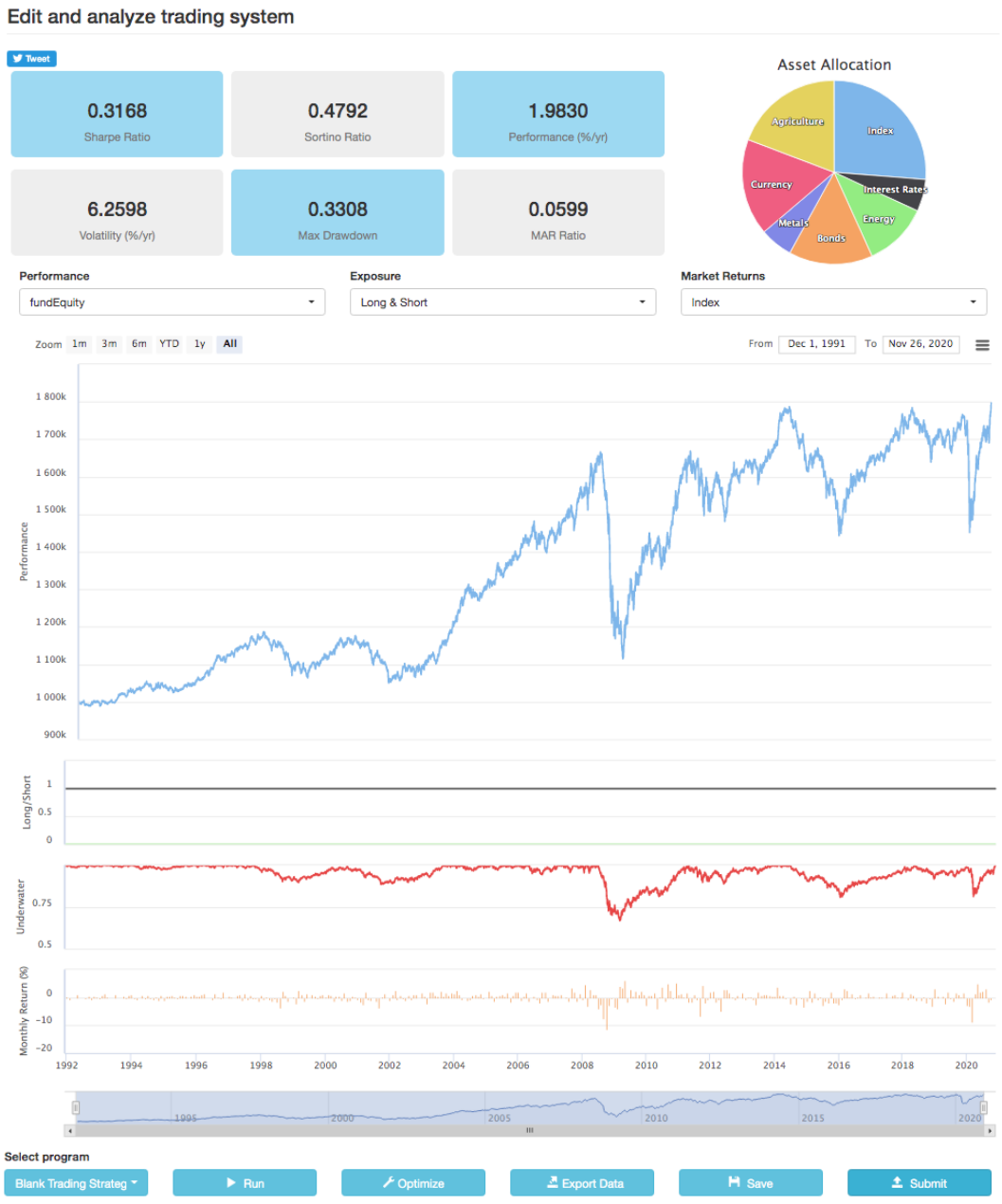
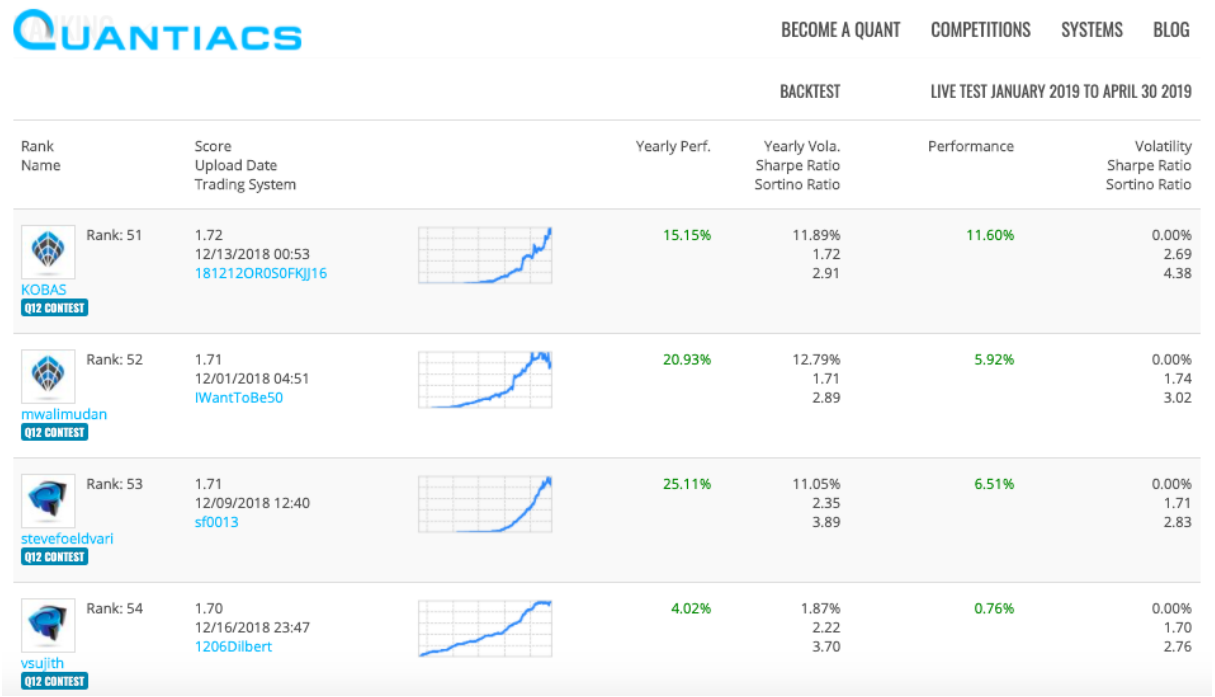


Figure IA.5: Contest Outcomes Revealed Once Live Period Ends. Excerpt from a contest leaderboard, showing both in-sample and out-of-sample Sharpe Ratios, after a trading contest has ended. The "live test" performance metrics were calculated once the contest period (1 January to 30 April 2019, in this case) had ended.



D Additional Figures for Trading Contest Analyses

Cross-Sectional Dispersion in OOS Performance Outcomes. Figure IA.6 illustrates the cross-sectional dispersion in the Live/out-of-sample Sharpe Ratios of contestants' systematic trading strategies in all 12 contests in the contest leaderboard sample. These are conditioned by the contest index, and thus depict the time-varying conditional distribution of investor performance outcomes. Immediately, it is evident that this distribution is widely dispersed. Some investors are able to benefit substantially by implementing systematic trading strategies, with high empirical SR, while others experience negative SRs. The median empirical out-of-sample SR is negative for many contests. Since contestants within the same contest have exactly the same information set, this figure also illustrates the extent of model disagreement.

Participation and Attrition. Figure IA.7 shows that a high proportion of contestants in each contest are first-time participants and that, furthermore, many participate only once. The latter fact is consistent with the prior literature and intuition discussed by Linnainmaa (2011). One important conclusion from this chart is that investors do not appear to be noticeably more or less willing to participate in contests just before or after the new macro predictive signals were introduced in between contests 7 & 8; i.e. macro signal availability does not appear to change participation patterns in a way that would mechanically generate an experience gradient.

Informativeness vs. Familiarity at the Individual Macro Signal Level. Figure IA.8 illustrates to what extent the aggregate individual macro variable informativeness and familiarity indices are concentrated among the top 3 and top 10 ranked individual variables each year. Familiarity is highly concentrated, while informativeness is more evenly-spread. Figure IA.9 displays the correlations of individual macroeconomic variables' rankings of informativeness and familiarity, recomputed each year. Both familiarity measures are highly correlated at the individual variable level. Variables' informativeness and familiarity are only weakly correlated with one another; still the correlation is typically positive.

Figure IA.6: Cross-Section of Out-of-Sample Performance Outcomes. Box-and-whisker plots of the distributions of Live (out-of-sample) trading strategy entry Sharpe Ratios, conditioning by contest index. The LHS plot shows all available entries; the RHS plot shows the best live entries per contest. Boxes cover the 25th and 75th percentiles of the empirical distribution; black dots denote the median value.

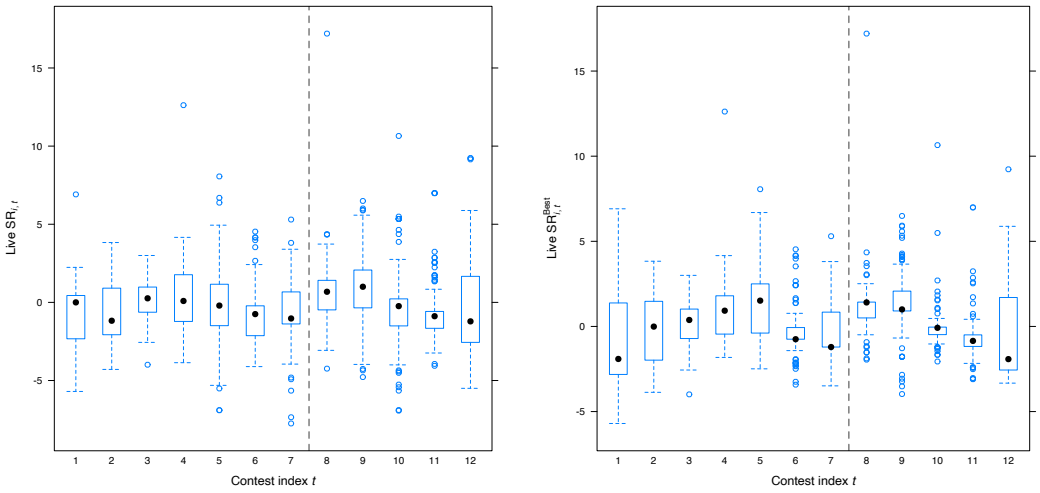


Figure IA.7: Participation and Attrition. Proportions of contestants for whom this is the first contest, and those for whom this is the last contest (with breakdowns of the latter).

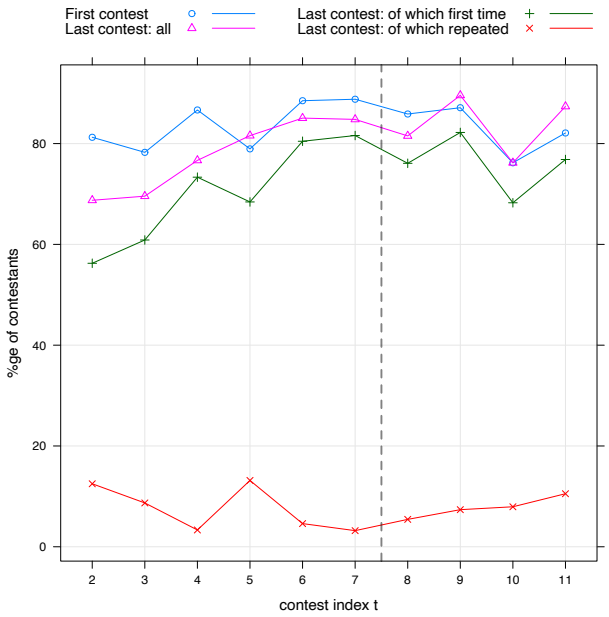


Figure IA.8: Concentration Measures of Individual Macro Signal Informativeness and Familiarity. Percentages of the total annual macro variable informativeness, and of the total annual macro variable mentions in news articles and books (i.e. familiarity), that are attributed to the top 3-ranked (LHS) and top 10-ranked (RHS) individual macro variables, for each year.

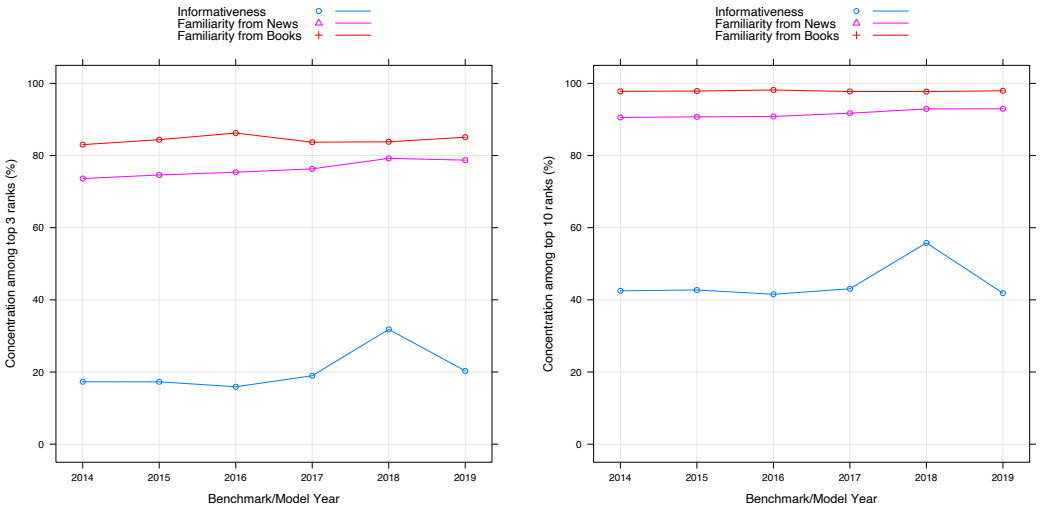
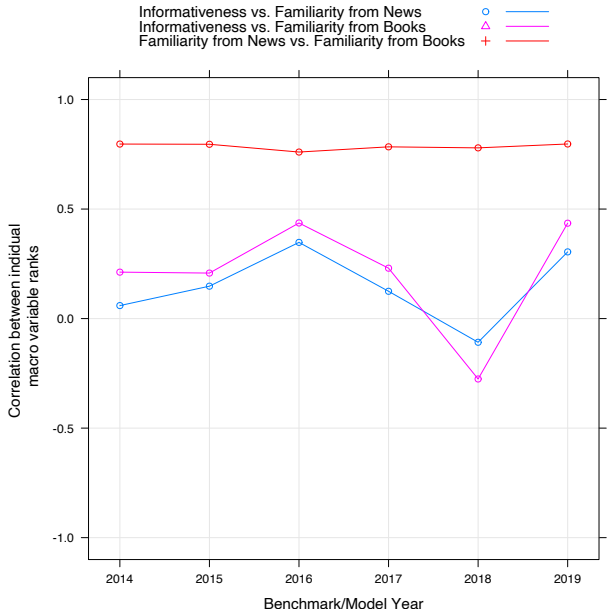


Figure IA.9: Rank-correlations of Individual Macro Signal Informativeness and Familiarity. Correlations between macro variable informativeness and familiarity rankings. For both familiarity measures, rankings are computed each year using article and book mentions for that year. The informativeness measures are computed according to a benchmark machine learning model that uses historical data up to the end of the prior year.



E Futures Contracts and the Benchmark Portfolio

As discussed in Section 2 of the paper, the Quantiacs trading platform allowed investors to take positions in 88 futures contracts, provided investors with historical market data for this investment universe, and used live market data during the out-of-sample evaluation period for each contest. For each future, the trading platform selected a single contract maturity that was available for trading at each point in time.

E.1 Futures Contract Prices

Like the platform, I use actual market data for the same universe of futures contracts, with the exception of the Russell 2000 index future, for which I simply use the daily index level.[20] I source the data from Bloomberg, stitching together multiple actively-traded futures contracts in a contiguous ratio-adjusted daily price series; this standard methodology ensures that return calculations are accurate. The futures (and their Bloomberg identifiers) are listed in Table IA.2.

Table IA.2: Futures Contracts. Futures instruments available on Quantiacs for contestants' trading strategies to take daily positions in. These are also the instruments I used to construct the benchmark index.

	Quantiacs ticker	Name	Type	Matching Bloomberg base code
1	F_AD	Australian Dollar	Currency	AD Curncy
2	F_AE	AEX Index	Index	EO Index
3	F_AH	Bloomberg Commodity Index	Index	DN Index
4	F_AX	DAX	Index	GX Index
5	F_BC	Brent Crude Oil	Energy	CO Comdty
6	F_BG	Gas Oil	Energy	QS Comdty
7	F_BO	Soybean Oil	Agriculture	BO Comdty
8	F_BP	British Pound	Currency	BP Curncy
9	F_C	Corn	Agriculture	C Comdty
10	F_CA	CAC40	Index	CF Index
11	F_CC	Cocoa	Agriculture	CC Comdty

[20] I use the Russell 2000 index itself to proxy for the series of Russell 2000 index futures contracts because I am unable to source and combine price data for these futures contracts: the Russell 2000 index future has changed its listing multiple times between the ICE and CME exchanges and I do not have access to older historical data. I judge it more useful for my benchmark to possess a long timeseries of the underlying index over the full backtest and live periods. Any gap or "basis" between the derivative price and underlying will be minimal because the most-active index future contract is typically the closest to maturity.

	Quantiacs ticker	Name	Type	Matching Bloomberg base code
12	F_CD	Canadian Dollar	Currency	CD Curncy
13	F_CF	10y Swiss Note	Bond	SWC Comdty
14	F_CL	WTI Crude Oil	Energy	CL Comdty
15	F_CT	Cotton	Agriculture	CT Comdty
16	F_DL	Milk Class III	Agriculture	DA Comdty
17	F_DM	MDAX Index	Index	MF Index
18	F_DT	EURO Bond	Bond	RX Comdty
19	F_DX	US Dollar Index	Currency	DX Curncy
20	F_DZ	TechDAX	Index	DP Index
21	F_EB	3-Month EuriBor	Interest Rate	ER Comdty
22	F_EC	Euro FX	Currency	EC Curncy
23	F_ED	Eurodollars	Interest Rate	ED Comdty
24	F_ES	E-mini S&P 500 Index	Index	ES Index
25	F_F	3-Month EuroSwiss	Interest Rate	ES Comdty
26	F_FB	DJ Stoxx Bank 600	Index	BJ Index
27	F_FC	Feeder Cattle	Agriculture	FC Comdty
28	F_FL	Chicago Ethanol	Energy	CUA Comdty
29	F_FM	Stoxx Europe Mid 200	Index	SXR Index
30	F_FP	OMX Helsinki 25	Index	OT Index
31	F_FV	5-year Treasury Note	Bond	FV Comdty
32	F_FY	Stoxx Europe 600	Index	SXO Index
33	F_GC	Gold	Metal	GC Comdty
34	F_GD	Goldman Sachs Commodity Index	Index	GI Index
35	F_GS	10-Year Long Gilt	Bond	G Comdty
36	F_GX	Euro BUXL	Bond	UB Comdty
37	F_HG	Copper	Metal	HG Comdty
38	F_HO	Heating Oil	Energy	HO Comdty
39	F_HP	Natural Gas Penultimate	Energy	ZA Comdty
40	F_JY	Japanese Yen	Currency	JY Curncy
41	F_KC	Coffee	Agriculture	KC Comdty
42	F_LB	Lumber	Agriculture	LB Comdty
43	F_LC	Live Cattle	Agriculture	LC Comdty
44	F_LN	Lean Hogs	Agriculture	LH Comdty
45	F_LQ	Newcastle Coal	Energy	XW Comdty
46	F_LR	Brazilian Real	Currency	BR Curncy
47	F_LU	Rotterdam Coal	Energy	XA Comdty
48	F_LX	FTSE 100 Index	Index	Z Index
49	F_MD	E-mini S&P 400	Index	FA Index
50	F_MP	Mexican Peso	Currency	PE Curncy
51	F_ND	New Zealand Dollar	Currency	NV Curncy
52	F_NG	Natural Gas	Energy	NG Comdty

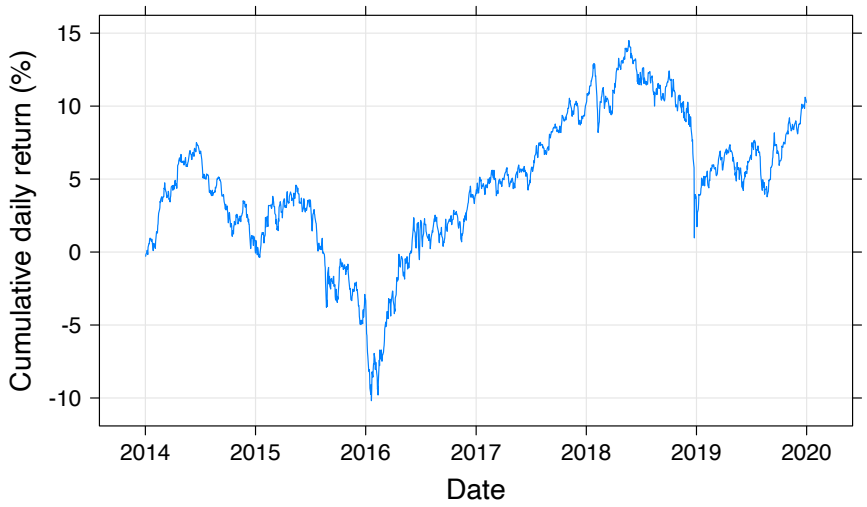
	Quantiacs ticker	Name	Type	Matching Bloomberg base code
53	F_NQ	E-mini Nasdaq 100 Index	Index	NQ Index
54	F_NR	Rough Rice	Agriculture	RR Comdty
55	F_NY	Nikkei 225	Index	NI Index
56	F_O	Oats	Agriculture	O Comdty
57	F_OJ	Orange Juice	Agriculture	JO Comdty
58	F_PA	Palladium	Metal	PA Comdty
59	F_PL	Platinum	Metal	PL Comdty
60	F_PQ	PSI20	Index	PP Index
61	F_RB	Gasoline	Energy	XB Comdty
62	F_RF	EURO FX/Swiss Franc	Currency	RF Curncy
63	F_RP	EURO FX/British Pound	Currency	RP Curncy
64	F_RR	Russian Ruble	Currency	RU Curncy
65	F_RU	Russell 2000	Index	RTY Index
66	F_RY	EURO FX/Japanese Yen	Currency	RY Curncy
67	F_S	Soybeans	Agriculture	S Comdty
68	F_SB	Sugar	Agriculture	SB Comdty
69	F_SF	Swiss Franc	Currency	SF Curncy
70	F_SH	Swiss Mid Cap	Index	S1 Index
71	F_SI	Silver	Metal	SI Comdty
72	F_SM	Soybean Meal	Agriculture	SM Comdty
73	F_SS	3-Month Short Sterling	Interest Rate	L Comdty
74	F_SX	Swiss Market	Index	SM Index
75	F_TR	South African Rand	Currency	RA Curncy
76	F_TU	2-year Treasury Note	Bond	TU Comdty
77	F_TY	10-year Treasury Note	Bond	TY Comdty
78	F_UB	EURO Bobl	Bond	OE Comdty
79	F_US	30-year Treasury Bond	Bond	US Comdty
80	F_UZ	EURO Schatz	Bond	DU Comdty
81	F_VF	5-Year Euro Swapnote	Bond	T Comdty
82	F_VT	10-Year Euro Swapnote	Bond	P Comdty
83	F_VW	2-Year Euro Swapnote	Bond	RW Comdty
84	F_VX	Volatilty Index	Index	UX Index
85	F_W	Wheat	Agriculture	W Comdty
86	F_XX	Dow Jones STOXX 50	Index	VG Index
87	F_YM	E-mini Dow Jones Industrial Average	Index	DM Index
88	F_ZQ	30-Day Fed Funds	Interest Rate	FF Comdty

E.2 Benchmark Portfolio to Adjust for Market Conditions

The trading platform does not formally judge contestants against a benchmark, though it does provide each contestant with an example systematic trading strategy that takes equally-weighted long positions in each of the 88 futures contracts available on the platform (Figure IA.3). Benchmark indices exist for certain sectors – such as the 24-contract Goldman Sachs Commodity Index (GSCI) – but I am not aware of any benchmark for futures as an overall asset class. I therefore construct the benchmark similarly to the simple default trading strategy suggested by Quantiacs to new users: based on daily-rebalanced equally-weighted returns of long positions in the most-active contracts of the underlying 88 futures (or, in the special case of the Russell 2000 index, the future's underlying index itself). A timeseries of returns for the benchmark portfolio is displayed in Figure IA.10.

Besides the fact that this benchmark portfolio is the default presented to new users, the methodology has additional merits. The use of long-only positions (similar to the GSCI commodity index methodology) is justified because the buyers of futures contracts receive delivery of the underlying physical/cash asset at maturity. The use of equally-weighted positions is justified by the absence of any alternative for weighting derivatives in such diverse underlying assets: unlike stocks or bonds, there is no fixed supply that limits the open interest that is possible in futures contracts.

Figure IA.10: Benchmark Portfolio. Cumulative return of the benchmark portfolio over the years in which contest Live periods took place.



F Macro Signals Available in a Subset of Trading Contests

On 22 March 2017, Quantiacs announced in a blog post that 54 macroeconomic data series would be made available to all contestants from the 8th contest onwards, for use in both backtesting and live trading. The variables are listed in Table IA.3.

Table IA.3: Macroeconomic Signals. Macroeconomic signals added to the Quantiacs platform from the 8th trading contest onwards, which could be used as input predictive variables for all contestants' trading strategies from that contest onwards.

	Macroeconomic variable	**Quantiacs identifier**
1	ADP Employment Change	USA_ADP
2	Average Hourly Earnings	USA_EARN
3	Average Weekly Hours	USA_HRS
4	Balance of Trade	USA_BOT
5	Business Confidence	USA_BC
6	Business Inventories	USA_BI
7	Capacity Utilization	USA_CU
8	Capital Flows	USA_CF
9	Challenger Job Cuts	USA_CHJC
10	Chicago Fed National Activity Index	USA_CFNAI
11	Chicago Pmi	USA_CP
12	Consumer Credit	USA_CCR
13	Consumer Price Index CPI	USA_CPI
14	Core Consumer Prices	USA_CCPI
15	Core Inflation Rate	USA_CINF
16	Dallas Fed Manufacturing Index	USA_DFMI
17	Durable Goods Orders	USA_DUR
18	Durable Goods Orders Ex Transportation	USA_DURET
19	Export Prices	USA_EXPX
20	Exports	USA_EXVOL
21	Factory Orders Ex Transportation	USA_FRET
22	Foreign Bond Investment	USA_FBI
23	Government Budget Value	USA_GBVL
24	Government Payrolls	USA_GPAY
25	Housing Index	USA_HI
26	Import Prices	USA_IMPX
27	Imports	USA_IMVOL
28	Industrial Production	USA_IP
29	Industrial Production Mom	USA_IPMOM
30	Inflation Rate	USA_CPIC
31	Inflation Rate Mom	USA_CPICM

	Macroeconomic variable	Quantiacs identifier
32	Job Offers	USA_JBO
33	Labor Force Participation Rate	USA_LFPR
34	Leading Economic Index	USA_LEI
35	Manufacturing Payrolls	USA_MPAY
36	Manufacturing Production	USA_MP
37	Nahb Housing Market Index	USA_NAHB
38	Net Long Term Tic Flows	USA_NLTTF
39	NFIB Business Optimism Index	USA_NFIB
40	Non Farm Payrolls	USA_NFP
41	Non Manufacturing PMI	USA_NMPMI
42	Nonfarm Payrolls Private	USA_NPP
43	NY Empire State Manufacturing Index	USA_EMPST
44	Pending Home Sales	USA_PHS
45	Philadelphia Fed Manufacturing Index	USA_PFED
46	Producer Prices	USA_PP
47	Producer Prices Change	USA_PPIC
48	Retail Sales MoM	USA_RSM
49	Retail Sales YoY	USA_RSY
50	Retail Sales Ex Autos	USA_RSEA
51	Richmond Fed Manufacturing Index	USA_RFMI
52	Total Vehicle Sales	USA_TVS
53	Unemployment Rate	USA_UNR
54	Wholesale Inventories	USA_WINV

F.1 Confirming Contestant Strategies Respond to Macro Signal Updates

Trading Activity Responses to Macro Signal Releases. I analyze the responses of investors' trading strategy turnovers to the release/update of macroeconomic variables on the platform. As a placebo test, I repeat this analysis for strategies submitted in earlier contests, when these macroeconomic indicators were not yet available on the platform (see Figure 2 in the paper).

I regress standardized daily trading volumes against various indicators for experience, the occurrence of macro release days, the availability of macro data in the current contest, and their interactions, and present the results in Table IA.4. The first two columns focus on strategies submitted in contests in which the macroeconomic predictive variables were available on the platform. The coefficient on the interaction in column (2) is positive and significant, indicating that experienced investors with access to the macro predictive variables trade significantly more on macro release days than on other days, relative to their inexperienced peers.This validation supports the use of release-day turnover as a measure that reveals signal adoption. The experience differential motivates the main tests of whether experienced investors respond more to informative release days.

The second two columns in Table IA.4 use the placebo sample of strategies from earlier contests, when macro signals were not yet available on the Quantiacs platform. The coefficient on the interaction in column (4) is not significantly different to zero: there was no significant above- or below-average change to the placebo group investors' daily trading volumes on the days the macro variables would have been released to the platform (in the counterfactual situation of them entering that trading strategy to a later contest).

This analysis suggests that investors' trading strategies respond to the release of macroeconomic predictive variables. There is also a differential response based on the human investors' experience. For the placebo in which macroeconomic indicators were not available, there was no discernible response by the trading strategies implemented by either experienced or inexperienced human investors on macro release days.

Heterogeneity in Reaction to Predictive Signal Informativeness. Armed with my index (7) of the predictive informational content of macro release days, I measure the sensitivity of different trading strategies to identical predictive signals. Using Eqn. (1), I compute the daily trading volumes of individual strategies i on historical calendar days τ. I then standardize this volume within-strategy, so that these z-scores are in comparable units across strategies. Then, for each strategy i, I conduct the following individual time series regression over the subset of

Table IA.4: Daily Trading Volume and Macro Signal Release Days. Regressions of standardized trading strategy daily volume against an indicator for the daily release of macro variables to contestants interacted with an indicator for experienced investors (who are taking part in their 3rd or 4th contest). Columns 1–2 use trading strategies from contests in which macro signals were available. Columns 3–4 use trading strategies from earlier contests in which macro variables were not available.

	$\text{Volume}_{i,\tau}$			
	With data availability		*Placebo group*	
	(1)	(2)	(3)	(4)
(Intercept)	0.002***	0.003***	0.002***	0.002***
	(0.0004)	(0.0001)	(0.001)	(0.001)
$\text{Macro Release}_{\tau}$	−0.009***	−0.011***	0.0002	0.0002
	(0.003)	(0.002)	(0.012)	(0.012)
$\text{Experienced}_{i,t}$		−0.009		0.0001
		(0.007)		(0.001)
$\text{Macro Release}_{\tau} \times \text{Experienced}_{i,t}$		0.076**		0.001
		(0.036)		(0.017)
N	3,234,115	3,234,115	2,059,615	2,059,615

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

macro release days τ:

$$\text{Volume}_{i,\tau} = \alpha_i + \beta_i \times \text{Informativeness}_{\tau} + \epsilon_{i,\tau} \tag{42}$$

Each estimated coefficient $\widehat{\beta}_i$ captures the sensitivity of trading strategy i to the release of the predictive information contained in macroeconomic indicators.

Next, I conduct a cross-sectional analysis of the extent to which different interpretations of the same signals can explain heterogeneity in trading strategies' overall trading patterns. I conduct pairwise regressions that are variants of the specification

$$\underbrace{-\rho_{i,j}}_{\substack{\text{Trading} \\ \text{dissimilarity}}} = \gamma \times \underbrace{\delta(\widehat{\beta}_i, \widehat{\beta}_j)}_{\substack{\text{Disagreement} \\ \text{about macro} \\ \text{predictive info.}}} + \phi_t + \epsilon_{i,j}, \tag{43}$$

where $\rho_{i,j}$ measures the correlation between the daily turnover series of two trading strategies i, j that are matched based on being entered into the same trading contest t; self joins are

excluded ($i \neq j$). The negative of this pairwise correlation therefore measures the *dis*similarity in trading activity between i, j. The trading response coefficients $\widehat{\beta}_i, \widehat{\beta}_j$ are estimated according to Eqn. (42).

It remains to measure the dissimilarity in trading response coefficients, $\delta(\widehat{\beta}_i, \widehat{\beta}_j)$, which captures how much a pair of trading strategies i, j disagree about the predictive content of the same macroeconomic indicators. I begin by computing the absolute distance $|\widehat{\beta}_i - \widehat{\beta}_j|$ between coefficient values. Since this produces a skewed measure, I specify three log-like transformations: the natural logarithm (of non-zero absolute values), the log of one plus the absolute value, and the inverse hyperbolic sine (arcsinh) of the absolute value.

Table IA.5 presents regression results for each of the variants of Eqn. (43). As might be expected, the $\widehat{\gamma}$ coefficient estimates are positive (and significant), suggesting that disagreement in trading activity tracks differential interpretations of the same information. Importantly, the fractions of variation explained by all specifications (i.e. R^2 values) are substantial. Specifications without contest fixed effects (in columns 1, 3 & 5) all explain just over a third of total variation in trading activity. The fraction increases even further when contest fixed effects are added (in columns 2, 4 & 6), and within-R^2 values are of a similar magnitude to the overall fractions of variance explained.

These results confirm that a substantial portion of the heterogeneity in systematic trading activity is due to different interpretations of the same information; i.e. model disagreement (Cookson and Niessner, 2020), or differences in opinion. The true extent to which model disagreement drives trading activity is most likely even higher, since this analysis excludes differential responses to price-based informational content (which is more challenging to measure). It follows that, in the setting studied by this paper, investors specify widely different predictive models of the world. The main text examines how experience and behavioral frictions shape this predictive model specification process.

Table IA.5: Relating Differences in Trading Activity to Differential Interpretations of Information. OLS & panel regressions of pairwise dissimilarity in trading activity against pairwise differences in the response to identical predictive information releases. The outcome variable is the negative of the pairwise correlation of the daily trading volume of two systematic trading strategies (i, j). Trading strategies i, j are matched by trading contest index t to ensure they have access to identical information sets. The covariates each measure the distance between daily trading volume responses to the predictive information content of macro release days $(\widehat{\beta}_i, \widehat{\beta}_j)$, as measured using individual regressions for i, j.

Dependent Variable:	$-\rho_{i,j}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\big(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\big)$	0.0486***	0.0508***				
	(0.0030)	(0.0026)				
$\log\big(1 + \lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\big)$			0.2423***	0.2866***		
			(0.0225)	(0.0362)		
$\text{arcsinh}\big(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\big)$					0.1952***	0.2307***
					(0.0170)	(0.0258)
Intercept	✓		✓		✓	
Contest FEs		✓		✓		✓
N	19,640	19,640	21,512	21,512	21,512	21,512
R^2	34.3	38.0	33.8	42.0	34.5	42.8
Within R^2		37.1		41.6		42.4

Note: standard errors (in parentheses) are clustered by contest and contestant.
*p<0.1; **p<0.05; ***p<0.01

F.2 Daily Macro Signal Informativeness vs. Familiarity

Table IA.6 lists the top 20-ranked macro variables by informativeness and by each familiarity measure, aggregated over the benchmark period.

Table IA.6: Macro Signal Rankings by Informativeness and Familiarity. Top-20 ranked macroeconomic predictive variables, by informativeness and familiarity, utilizing the means of annual 2014-2019 rankings.

Rank	By Informativeness	By Familiarity (News)	By Familiarity (Books)
1	Export Prices	Exports	Exports
2	Imports	Imports	Imports
3	Producer Prices Change	Unemployment Rate	Unemployment Rate
4	Inflation Rate	Industrial Production	Industrial Production
5	Import Prices	Business Confidence	Inflation Rate
6	Capacity Utilization	Inflation Rate	Capital Flows
7	Exports	Consumer Credit	Consumer Credit
8	Balance of Trade	Capacity Utilization	Balance of Trade
9	Core Inflation Rate	Export Prices	Capacity Utilization
10	ADP Employment Change	Producer Prices	Job Offers
11	Government Payrolls	Import Prices	Export Prices
12	Consumer Price Index CPI	Capital Flows	Import Prices
13	Industrial Production	Consumer Price Index CPI	Labor Force Participation Rate
14	Unemployment Rate	Job Offers	Business Confidence
15	Non Farm Payrolls	Manufacturing Production	Producer Prices
16	Philadelphia Fed Manufacturing Index	Non Farm Payrolls	Manufacturing Production
17	Manufacturing Payrolls	Pending Home Sales	Average Hourly Earnings
18	Housing Index	Average Hourly Earnings	Average Weekly Hours
19	Average Weekly Hours	Durable Goods Orders	Business Inventories
20	Manufacturing Production	Business Inventories	Core Inflation Rate

G Robustness Checks for Trading Contest Analyses

G.1 Crash Risk

This section tests whether experienced investors' strategies have a higher exposure to crash risk. Table IA.7 summarizes available daily returns into various trading strategy-level indicators for crash risk and compares them with investor experience.

Table IA.7: Crash Risk Versus Experience. For each trading strategy entry, Crash Days is the number of days per 250-day year in which the daily return is less than 3 units of return standard deviations below the mean, |MIN1| is the absolute value of the lowest (most negative) daily return, |MIN5| is the mean of the absolte values of the 5-lowest daily returns, and Skewness is also computed from all available daily returns of each trading strategy.

Dep. Vars.:	Crash Days (1)	|MIN1| (2)	|MIN5| (3)	Skewness (4)
Contests Experienced$_{i,t}$	-0.4512***	0.3130	0.1105	-0.2347
	(0.1057)	(1.167)	(0.9141)	(0.4744)
Contest FEs	✓	✓	✓	✓
Contestant FEs	✓	✓	✓	✓
N	721	721	721	721
R^2	95.37	89.76	90.99	95.95

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

G.2 Competitive Intensity

This section tests whether competitive intensity could be a driver of contestant effort. I measure competitive intensity as the (log of the) number of contestants taking part in a given contest.

Table IA.8 shows Poisson GLM regressions that find no significant association between an investor's observed effort and the competitive pressures she experiences, controlling for her experience level. Furthermore, there is also no significant interaction with the availability of macro signals. Note that these regression specifications deliberately do not apply any clustering to standard errors, in order to set a lower hurdle for coefficient significance to overcome; nonetheless, competitive intensity does not enter into the regression specifications with any significance.

Table IA.8: Effort and Competitive Intensity. Poisson GLM regressions of contestants' number of entries in a contest against measures of experience, availability of additional predictive variables, and competitive intensity. The indicator "Macro Signals Available$_t$" equals one for Treatment observations and zero for Control observations, as defined in Section 5.2.

	Dependent variable:			
	Entries$_{i,t}$			
	(1)	(2)	(3)	(4)
(Intercept)	0.737***	1.085**	1.080**	0.885*
	(0.074)	(0.435)	(0.460)	(0.502)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	0.812***	0.794***	0.794***	0.792***
	(0.168)	(0.172)	(0.172)	(0.173)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	1.537***	1.523***	1.523***	1.505***
	(0.350)	(0.352)	(0.353)	(0.347)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	2.070***	2.070***	2.069***	2.055***
	(0.389)	(0.393)	(0.398)	(0.393)
Log Contestants$_t$		−0.077	−0.075	−0.027
		(0.094)	(0.107)	(0.115)
Macro Signals Available$_t$			−0.004	1.138
			(0.157)	(1.267)
Macro Signals Available$_t$ × Log Contestants$_t$				−0.249
				(0.270)
N	830	830	830	830

Note: standard errors (in parentheses) are robust to heteroskedasticity.
*p<0.1; **p<0.05; ***p<0.01

G.3 Controlling for Entry Count

In this section, Table IA.9 augments the primary out-of-sample specification in Table 2 (column 1) with controls for the number of entries (columns 2–3).

Table IA.9: Experience–Performance Gradient Controlling for Entry Counts. This table shows regressions of out-of-sample (Live) Sharpe Ratios (SRs) against experience, controlling for the number of trading strategy entries made into the current contest and prior contests.

Dependent Variable:	Live $SR_{i,t}$		
	(1)	(2)	(3)
Contests Experienced$_{i,t}$	1.261***	1.152***	1.161**
	(0.2750)	(0.2849)	(0.4129)
Entries in Current Contest$_{i,t}$		0.0511	0.0509
		(0.0294)	(0.0294)
Prior Entries$_{i,t}$			-0.0006
			(0.0070)
Contest FEs	✓	✓	✓
Contestant FEs	✓	✓	✓
N	874	874	874
R^2	83.42	83.93	83.93

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

G.4 Official Scores

This appendix repeats key results based on contestants' out-of-sample (Live) Sharpe ratios as dependent variables and instead uses the official scores assigned by the Quantiacs platform, which are defined to be the minimum of the in-sample (Backtest) and out-of-sample (Live) Sharpe ratios:

- Table IA.10 modifies the specification of Table 2 in the main paper.
- Table IA.11 modifies the specification of Table 8 in the main paper.
- Table IA.12 modifies the specification of Table 9 in the main paper.

There is little change to the estimates and no change to the conclusions drawn.

Table IA.10: Trading Contest Performance Outcomes Increase with Accumulated Experience, Showing Official Scores. This table shows regressions of Quantiacs' assigned Official Scores against experience, as a robustness check.

Dependent Variable:	Official Score$_{i,t}$		
	(1)	(2)	(3)
Contests Experienced$_{i,t}$	0.3701**	0.3743**	0.8980***
	(0.1299)	(0.1249)	(0.1634)
Intercept	✓		
Contest FEs		✓	✓
Contestant FEs			✓
N	874	874	874
R^2	6.67	25.12	88.50

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table IA.11: Experience Gradient in Gains from Macro Signal Availability. Regressions of investors' official scores against additional data availability interacted with experience. The dependent variable in columns (1)-(3) does not incorporate a benchmark, so there is no control for time periods; the dependent variable in columns (4)-(6) is the excess official score over the Sharpe Ratio of the benchmark index during the matched time period, which effectively controls for time periods/contests. The indicator "Macro Signals Available$_t$" equals one for Treatment observations and zero for Control observations, as defined in Section 5.2.

	Dependent variable:					
	Score$_{i,t}$			Score$_{i,t}$ − Benchmark SR$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	−0.592**	−0.716***	−0.698***	−2.002***	−1.754***	−1.704***
	(0.232)	(0.127)	(0.133)	(0.376)	(0.350)	(0.367)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	0.678***	0.703***	0.671***	0.945***	0.895***	0.840***
	(0.221)	(0.192)	(0.255)	(0.192)	(0.201)	(0.244)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	0.920	0.932	0.644***	1.746***	1.722***	0.571*
	(0.585)	(0.573)	(0.209)	(0.435)	(0.420)	(0.323)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	2.493***	2.560***	2.020***	2.770***	2.637***	1.530***
	(0.675)	(0.577)	(0.426)	(0.731)	(0.704)	(0.444)
Macro Signals Available$_t$		0.201	0.172		−0.403	−0.483
		(0.342)	(0.384)		(0.660)	(0.667)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\} \times$ Macro Signals Available$_t$			0.057			0.092
			(0.382)			(0.407)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\} \times$ Macro Signals Available$_t$			0.515			2.063***
			(1.034)			(0.626)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\} \times$ Macro Signals Available$_t$			1.856**			3.783***
			(0.855)			(0.511)
N	830	830	830	830	830	830
R^2	6.1	6.8	7.2	6.5	8.0	9.7

Note: standard errors (in parentheses) are clustered by contest and contestant. *p<0.1; **p<0.05; ***p<0.01

Table IA.12: Selection Effects Do Not Explain the Experience Gradient: Heckman Two-Stage Estimates. Heckman (1976) (i.e. Type II Tobit) two-stage selection models for implementing selection bias corrections to the regression of official score against experience. The first stage models the probability of participation. The second stage models the outcome of interest.

		All contests	*Contests 1-7*	*Contests 8-12*
Stage		$\text{Score}_{i,t}$	$\text{Score}_{i,t}$	$\text{Score}_{i,t}$
1. *Selection*	(Intercept)	1.95^{***}	2.38^{***}	1.50^{***}
		(0.18)	(0.29)	(0.34)
	$\text{Contests Experienced}_{i,t}$	-0.88^{***}	-1.22^{***}	-0.77^{***}
		(0.05)	(0.10)	(0.05)
	$\text{Quantopian Search Index}_{t}$	-0.01^{**}	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
	$\text{Ratio of Entries to Contest Mean}_{i,t-1}$	0.23^{***}	0.24^{***}	0.22^{***}
		(0.04)	(0.08)	(0.04)
2. *Outcome*	(Intercept)	-0.99^{***}	-0.85^{***}	-0.14
		(0.08)	(0.30)	(0.14)
	$\text{Contests Experienced}_{i,t}$	0.75^{***}	0.51	0.70^{***}
		(0.11)	(0.36)	(0.17)
	Inverse Mills Ratio	-0.76^{***}	0.39	-0.94^{***}
		(0.19)	(0.49)	(0.36)
	σ	1.33	1.74	2.00
	ρ	-0.57	0.22	-0.47
	R^2	9	9	4
	Num. obs.	1482	482	1000
	Censored	621	163	458
	Observed	861	319	542

Standard errors (in parentheses) computed according to Greene (1981). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

H Stock Characteristics Used to Construct Predictive Signals

Table IA.13 describes the 208 stock-level characteristics collected by Chen and Zimmermann (2022) for which a publication date can be defined. These characteristics are used to construct decile-based return predictability signals in the main text.

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
AM	Total assets to market	Accounting	Total assets (at) divided by market value of equity.	Fama and French (1992)
AOP	Analyst Optimism	Analyst	AnalystValue minus IntrinsicValue (defined in Chen and Zimmermann (2022)), divided by abs(IntrinsicValue).	Frankel and Lee (1998)
AbnormalAccruals	Abnormal Accruals	Accounting	Define Accruals as net income (ib) minus operating cash flow (oancf), divided by average total assets (at) for years t-1 and t. If oancf is missing, replace operating cash flow with funds from operations (fopt) minus the annual change in total current assets (act) plus the annual change in cash and short-term investments (che) plus the annual change in current liabilities (lct) minus the annual change in debt in current liabilities (dlc). For each year t and 2-digit sic code, regress Accruals on: the inverse of average total assets for year t-1, the change in revenue (sale) from year t-1 to t divided by total assets for t-1, propery plant and equipment (ppegt) divided by total assets for t-1. AbnormalAccrual is the residual from this cross-sectional regression. See code for more details.	Xie (2001)
Accruals	Accruals	Accounting	Annual change in current total assets (act) minus annual change in cash and short-term investements (che) minus annual change in current liabilities (lct) minus annual change in debt in current liabilities (dlc) minus change in income taxes (txp). All divided by average total assets (at) over this year and last year. Exclude if abs(prc) < 5.	Sloan (1996)
AccrualsBM	Book-to-market and accruals	Accounting	Binary variable equal to 1 if stock is in the highest Accrual quintile and the lowest BM quintile, and equal to 0 if stock is in the lowest Accrual quintile and the highest BM quintile. Exclude if book equity (ceq) is negative.	Bartov and Kim (2004)
Activism1	Takeover vulnerability	13F	24 minus Governance Index (G). Set to missing if G is missing, or if not in the highest quartile of institutional ownership (maxinstown_perc), or if dual share class.	Cremers and Nair (2005)
Activism2	Active shareholders	13F	Instituitional ownership share (maxinstown_perc) if share greater than 5 percent. Set to missing if G is missing, or if dual share class, or if 24 minus Governance index (G) is less than 19.	Cremers and Nair (2005)
AdExp	Advertising Expense	Accounting	Advertising expense (xad) over market value of equity (shrout*abs(prc))	Chan, Lakonishok and Sougiannis (2001)
AgeIPO	IPO and age	Event	Age is (current year - founding year from Jay Ritter's dataset). Exclude if IndIPO == 0.	Ritter (1991)
AnalystRevision	EPS forecast revision	Analyst	keep fpi == "1", last obs each month. Signal is meanest / last month's meanest.	Hawkins, Chamberlin, Daniel (1984)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
AnalystValue	Analyst Value	Analyst	Value based on a three-stage dividend discount model and analyst forecasts, scaled by market value. See code for details.	Frankel and Lee (1998)
Announcement-Return	Earnings announcement return	Price	Get announcement date for quarterly earnings from IBES (fpi = 6). AnnouncementReturn is the sum of (ret - mktrf + rf) from one day before an earnings announcement to 2 days after the announcement.	Chan, Jegadeesh and Lakonishok (1996)
AssetGrowth	Asset growth	Accounting	Annual growth rate of total assets (at)	Cooper, Gulen and Schill (2008)
BMdec	Book to market using December ME	Accounting	BM using most recent December value of market equity.	Fama and French (1992)
BPEBM	Leverage component of BM	Accounting	BP - EBM, where BP = (ceq + tstkp - dvpa)/(shrout*abs(prc)), and EBM is defined separately. Exclude if price less than 5.	Penman, Richardson and Tuna (2007)
Beta	CAPM beta	Price	Coefficient of a 60-month rolling window regression of monthly stock returns minus the riskfree rate on market return minus the risk free rate (ewretd - rf). Exclude if estimate based on less than 20 months of returns.	Fama and MacBeth (1973)
BetaFP	Frazzini-Pedersen Beta	Price	Using daily data, call tempRi the sum of today's return and the past 2 days, call tempRm the sum of today's mkt return and the past 2 days mkt return. Regress return on tempRi and tempRm using past 5 years of data, with a minimum of 3 years. BetaFP is the square root of the r square from this regression times the ratio of the idiosyncratic stock vol and the market vol.	Frazzini and Pedersen (2014)
BetaLiquidityPS	Pastor-Stambaugh liquidity beta	Price	Monthly excess return (ret -rf) regressed on innovations in liquidity from Pastor's website (`https://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2018.txt`). Use 60 month rolling window regression, and require at least 36 non-missing observations.	Pastor and Stambaugh (2003)
BetaTailRisk	Tail risk beta	Price	Each month, compute the 5th percentile over daily returns over all firms. For all daily return observations with return below that 5th percentile, compute the average of (log(ret/5th percentile of cross-sectional return distribution). Call that average tailEX. BetaTailRisk is the coefficient of a 120-month rolling regression of a firm's stock return on tailEX. Exclude if price less than 5 or share code greater than 11.	Kelly and Jiang (2014)
BidAskSpread	Bid-ask spread	Trading	Effective bid ask spread based on Corwin-Schulz scaled by stock price.	Amihud and Mendelson (1986)
BookLeverage	Book leverage (annual)	Accounting	Total assets (at) divided by book value of equity plus deferred taxes (txditc) and preferred stock. Equity is shareholder equity (seq) if available, or book equity (ceq) plus preferred stock (pstk, if missing pstkrv, if missing pstkl), or total assets minus total liabilities (lt).	Fama and French (1992)
BrandInvest	Brand capital investment	Accounting	Advertising expenses (xad) divided by BrandCapital. Brand capital is computed by the perpetual inventory method. In the first year, brand capital is advertising expense divided by (.5 + .1). In subsequent years, we let brand capital depreciate with a rate of .5 and add current advertising expenses. Brand capital is scaled by total assets (at). Set to missing if advertising expense is missing. Drop if 1st digit of sic = 4 or 6, and keep only Dec fiscal year ends.	Belo, Lin and Vitorino (2014)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
CBOperProf	Cash-based operating profitability	Accounting	Revenue (revt) minus cost (cogs) - (administrative expenses (xsga) - R&D expenses (xrd)) minus annual change in receivables (rect), annual change in investment (invt) and annual change in prepaid expenses, plus annual change in current deferred revenue (drc), long-term deferred revenue (drlt), accounts payable (ap) and accrued expenses (xacc), all divided by total assets (at) in year t. Replace all variables in the numerator with 0 if they are missing. Exclude if share code is greater 11, market value of equity, BM or total assets are missing, or if SIC code between 6000 and 6999.	Ball et al. (2016)
CF	Cash flow to market	Accounting	Net income (ib) plus depreciation (dp) divided by market equity. Exclude NASDAQ stocks.	Lakonishok, Shleifer and Vishny (1994)
CPVolSpread	Call minus Put Vol	Options	ATM Call vol minus ATM put vol	Bali and Hovakimian (2009)
Cash	Cash to assets	Accounting	Ratio of quarterly cash and short-term investments (cheq) and total assets (atq).	Palazzo (2012)
ChAssetTurnover	Change in Asset Turnover	Accounting	Annual change in AssetTurnover (defined in Chen and Zimmermann (2022)). Exclude if price less than 5.	Soliman (2008)
ChEQ	Growth in book equity	Accounting	Ratio of book equity (ceq) to book equity in the previous year. Include only if book equity is positive this year and last year.	Lockwood and Prombutr (2010)
ChForecastAccrual	Change in Forecast and Accrual	Analyst	Within upper half of Accruals distribution, equal to 1 if mean earnings estimate increased relative to the previous month. 0 if it decreased.	Barth and Hutton (2004)
ChInv	Inventory Growth	Accounting	12 month change in inventory (invt) divided by average total assets.	Thomas and Zhang (2002)
ChInvIA	Change in capital inv (ind adj)	Accounting	Growth in capital expenditure (capx) minus average growth in capital expenditure in the same industry (two-digit SIC). If capx is missing, capital expenditure is defined as the annual change in property, plant and equipment (ppent). Capital expenditure growth is defined as the percentage growth of capx today relative to the average capx over the previous two years (.5*(capx_{t-1} + capx_{t-2}), or as percentage growth relative to the previous year only if t-2 is missing.	Abarbanell and Bushee (1998)
ChNAnalyst	Decline in Analyst Coverage	Analyst	Using IBES forecasts, keep if fpi = 1, fpedats not missing, and fpedats > statpers + 30. Binary variable equal to 1 if the number of analysts (numest) for next quarter's EPS estimate decreased relative to three months ago, and 0 if it increased. Keep if in bottom two size quintiles among all firms to match OP's table.	Scherbina (2008)
ChNNCOA	Change in Net Noncurrent Op Assets	Accounting	Twelve-month change in noncurrent operating assets. Noncurrent operating assets is ((at - act - ivao) - (lt - dlc - dltt))/at.	Soliman (2008)
ChNWC	Change in Net Working Capital	Accounting	Twelve-month change in net working capital. Net working capital is ((act - che) - (lct - dlc))/at	Soliman (2008)
ChTax	Change in Taxes	Accounting	4-quarter change in quarterly total taxes (txtq), scaled by lagged total assets (at).	Thomas and Zhang (2011)
ChangeIn-Recommendation	Change in recommendation	Analyst	keep last ireccd each month, then average across analysts for each firm-month. Define opscore as 6-ireccd. Signal is opscore - last month's opscore.	Jegadeesh et al. (2004)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
CitationsRD	Citations to RD expenses	Other	Drop obs before 1975. Set expenses for research and development (xrd) and number of citations (ncit) to 0 if missing. Calculate Citations to RD as sum of citations over previous 5 years divided by sum of xrd over years $t-3,\ldots,t-7$. Drop if denominator $=0$, 2 years or less in Compustat, sic in 6000s, ceq <0. Double independent sort using (a) size NYSE median (b) terciles of Citations to RD. Long if in small size, highest tercile of Citations to RD, short if in small size, smallest tercile.	Hirschleifer, Hsu and Li (2013)
CompEquIss	Composite equity issuance	Accounting	5 year growth rate of market value of equity minus 5 year stock return.	Daniel and Titman (2006)
CompositeDebtIssuance	Composite debt issuance	Accounting	Log of long-term debt (dltt) plus debt in current liabilties (dlc) minus log of the same variable 5 years ago.	Lyandres, Sun and Zhang (2008)
ConsRecomm	Consensus Recommendation	Analyst	Binary variable if the monthly mean of recommendations (ireccd) over analysts is greater than 3, and 0 if it is less or equal than 1.5.	Barber et al. (2001)
ConvDebt	Convertible debt indicator	Accounting	Binary variable equal to 1 if deferred charges (dc) greater than 0 or common shares reserved for convertible debt (cshrc) greater than 0.	Valta (2016)
CoskewACX	Coskewness using daily returns	Price	Signal is the sample counterpart of $E[\tilde{r}_{it}\tilde{r}_{mt}^2]/(SD[\tilde{r}_{it}]SD[\tilde{r}_{mt}]^2$ where $\tilde{r}_{it}$ is the de-meaned stock return and $\tilde{r}_{mt}$ is the de-meaned market excess return. Signal is computed using the past year of daily data, and using the NYSE CRSP VW index for the market (dsia), with returns continuously compounded. See code for details.	Ang, Chen and Xing (2006)
Coskewness	Coskewness	Price	Signal is the sample counterpart of $E[\tilde{r}_{it}\tilde{r}_{mt}^2]/(SD[\tilde{r}_{it}]SD[\tilde{r}_{mt}]^2$ where $\tilde{r}_{it}$ is the de-meaned stock excess return and $\tilde{r}_{mt}$ is the de-meaned market excess return. Signal is computed using the past 60 months of monthly data, and using the NYSE/AMEX CRSP VW index for the market (msic). See code for details.	Harvey and Siddique (2000)
CredRatDG	Credit Rating Downgrade	Analyst	A downgrade happens if credit rating (splticrm) decreased by at least one notch relative to the previous month. CredRatDG $=1$ if a downgrade happened over the past 3 months. OP studies Moody's ratings changes between 1970 and 1997, but our data doesn't begin in earnest until 1986, and our sample definitions apply to returns, and this predictor implicitly averages over the past 6 months.	Dichev and Piotroski (2001)
CustomerMomentum	Customer momentum	Other	Based on firms' principals customers from Compustat Segment data as in Cohen and Frazzini.	Cohen and Frazzini (2008)
DebtIssuance	Debt Issuance	Accounting	Equal to 1 if debt issuance (dltis) greater 0 and 0 otherwise. Exclude if share code >11 or missing book-to-market.	Spiess and Affleck-Graves (1999)
DelBreadth	Breadth of ownership	13F	Quarterly change in the number of institutional owners (numinstowners) from 13F data. Exclude if in the lowest quintile of stocks by market value of equity (based on NYSE stocks only).	Chen, Hong and Stein (2002)
DelCOA	Change in current operating assets	Accounting	Difference in current operating assets (total current assets (act) minus cash and short-term investments (che)) between years t-1 and t, scaled by average total assets (at) in years t-1 and t.	Richardson et al. (2005)
DelCOL	Change in current operating liabilities	Accounting	Difference in current operating liabilities (total current liabilities (lct) minus debt in current liabilities (dlc)) between years t-1 and t, scaled by average total assets (at) in years t-1 and t.	Richardson et al. (2005)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
DelDRC	Deferred Revenue	Accounting	Annual change in deferred revenue (drc) scaled by average total assets (at) in t-1 and t. Exclude if negative book equity (ceq), deferred revenue equal to 0 in both years, revenue less than 5m, or SIC code between 6000 and 6999.	Prakash and Sinha (2013)
DelEqu	Change in equity to assets	Accounting	Difference in book equity (ceq) between years t-1 and t, scaled by average total assets (at) in years t-1 and t.	Richardson et al. (2005)
DelFINL	Change in financial liabilities	Accounting	Difference in financial liabilities (sum of long-term debt (dltt), current liabilitites (dlc) and preferred stock (pstk)) between years t-1 and t, scaled by average total assets (at) in years t-1 and t.	Richardson et al. (2005)
DelLTI	Change in long-term investment	Accounting	Difference in investment and advances (ivao) between years t-1 and t, scaled by average total assets (at) in years t-1 and t.	Richardson et al. (2005)
DelNetFin	Change in net financial assets	Accounting	Compute the sum of short-term investments (ivst) and investments and advances (ivao) minus the sum of long-term debt (dltt), debt in current liabilities (dlc) and preferred stock capital. Divide the difference between the current and one-year lagged sum by total assets (at) averaged over the current and previous fiscal years.	Richardson et al. (2005)
DivInit	Dividend Initiation	Event	Keep only distcd 2nd digit = 2 or 3. Define dividend initiation as having paid a dividend in month t (divamt > 0), and not having paid a dividend in the last 24 months. DivInit is equal to 1 if a dividend was initiated in the past 6 months, and 0 for all other stocks.	Michaely, Thaler and Womack (1995)
DivOmit	Dividend Omission	Event	Keep only distcd 2nd digit = 2 or 3. Define firms as quarterly, semi-annual, or annual payers based on payment history. Define a consistent payer as a firm that paid quarterly or semi-annual dividends for the past 18 months, or annual dividends for the past 2 years. An omission is the first month where a consistent payer failed to pay a dividend over the past quarter/6-months/year. Finally, DivOmit = 1 if there is an omission in the past 2 months and 0 otherwise	Michaely, Thaler and Womack (1995)
DivSeason	Dividend seasonality	Event	Drop if 3rd digit of distcd = 2 or >= 6. Assign DivSeason = 0 if there was a dividend paid in the last 12 months. Replace DivSeason = 1 if the third digit of disctcd is 3, 0, or 1, and a positive dividend was paid 2, 5, 8, or 11 months ago, if the third digit is 4 and a dividend was paid 5 or 11 months ago, or if the third digit is 5 and a dividiend was paid 11 months ago.	Hartzmark and Salomon (2013)
DivYieldST	Predicted div yield next month	Accounting	Using CRSP distributions, keep only distcd beginning in 12 and if the third digit of distcd is 3, 4, or 5. Also keep only if stock paid a dividend in the last 12 months. Define Ediv1 = div 2 months ago if distcd's 3rd digit is 0, 1, or 3. Define Ediv1 = div 5 months ago if the distcd 3rd digit is 4. Define Ediv = div 11 months ago if the distcd 3rd digit is 5. Define Edy1 as Ediv1/abs(prc). Finally, discretize Edy1 to smooth around the huge mass at 0 as follows: DivYieldST = 0 if Edy1 = 0, 1 if Edy is between 0 and 0.005, 2 if Edy1 is between 0.005 and 0.010, and 3 if Edy > 0.010.	Litzenberger and Ramaswamy (1979)
DolVol	Past trading volume	Trading	Log of two-month lagged trading volume (vol) times two-month lagged price (prc).	Brennan, Chordia and Subramanyam (1998)
DownRecomm	Down forecast EPS	Analyst	Keep fpi = 1. Binary variable equal to 1 if mean analyst earnings forecast for the next quarter (meanest) has improved over the previous month, and 0 otherwise.	Barber et al. (2001)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
EBM	Enterprise component of BM	Accounting	(ceq + che - dltt - dlc - dc - dvpa+ tstkp) / (mve_c + che - dltt - dlc - dc - dvpa+ tstkp). Exclude if price less than 5.	Penman, Richardson and Tuna (2007)
EP	Earnings-to-Price Ratio	Accounting	ib / lag(market value of equity, 6 months). NYSE stocks only. Exclude if EP < 0. Lag simulates the Dec 31 market equity used in original paper	Basu (1977)
EarnSupBig	Earnings surprise of big firms	Accounting	Average monthly value of EarningsSurprise (defined separately) of the 30% largest companies by market value of equity in the same Fama-French 48 industry. Exclude the largest 30% of companies for EarnSupBig (not to compute the anomaly)	Hou (2007)
Earnings-Consistency	Earnings consistency	Accounting	Average earnings growth over previous 48 months. Earnings growth is defined as EPS (epspx) minus EPS 12 months ago divided by average EPS 12 and 24 months ago. Exclude if price less than 5, absolute value of 12 month earnings growth greater 600%, or earnings growth and earnings growth 12 months ago have different signs.	Alwathainani (2009)
EarningsForecast-Disparity	Long-vs-short EPS forecasts	Analyst	Analyst forecasted 5-year earnings growth (fgr5yr) minus 100 times the difference between mean earnings forecast (meanest) and fiscal year earnings expectations (fy0a) scaled by the absolute value of fy0a. Drop if fpedats is missing or fpedats - statpers < 30	Da and Warachka (2011)
EarningsStreak	Earnings surprise streak	Accounting	Use fpi == 6 and only the last statpers for each anndats_act. Define surp = (actual - meanest)/price. Define a firm-anndats as a streak if surp has the same sign as the most recent surp observation. Keep only streaks. Then define signal = surp.	Loh and Warachka (2012)
EarningsSurprise	Earnings Surprise	Accounting	EPS (epspxq) minus EPS twelve months ago - Drift, scaled by standard deviation of that expression. Drift is the average earnings growth (EPS - EPS twelve months ago) over the past two years. Exclude if price less than 5	Foster, Olsen and Shevlin (1984)
EntMult	Enterprise Multiple	Accounting	Market value of equity + long-term debt (dltt) + debt in current liabilities (dlc) + deferred charges (dc) - cash and short-term investments (che) , divided by operating income (oibdp). Exclude if missing book equity or negative operating income.	Loughran and Wellman (2011)
EquityDuration	Equity Duration	Accounting	see code	Dechow, Sloan and Soliman (2004)
ExchSwitch	Exchange Switch	Event	Binary variable equal to 1 if a firm switched from AMEX or NASDAQ to NYSE within the past year, or from NASDAQ to AMEX within the past year.	Dharan and Ikenberry (1995)
ExclExp	Excluded Expenses	Analyst	Difference between unadjusted earnings (EPSActualUnadj) from IBES and quarterly earnings per share (epspiq). Exclude the highest and lowest 1% of values.	Doyle, Lundholm and Soliman (2003)
FR	Pension Funding Status	Accounting	FR = (FVPA - PBO), scaled by market value of equity. FVPA is pbnaa from 1980 to 1986, pplao + pplao from 1987 to 1997, and pplao after 1997. PBO is pbnvv from 1980 to 1986, pbpro + pbpru from 1987 to 1997, and pbpro after 1997. Exclude if price less than 5 or shrcd > 11.	Franzoni and Marin (2006)
FirmAge	Firm age based on CRSP	Other	Months since start of CRSP coverage.	Barry and Brown (1984)
FirmAgeMom	Firm Age - Momentum	Price	6 month return, restricted to the bottom quintile of the cross-sectional firm age distribution. Exclude if price less than 5 or firm younger than 12 months.	Zhang (2006)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
ForecastDispersion	EPS Forecast Dispersion	Analyst	Keep fpi = 1 and fpedats > statpers + 30. Standard deviation of earnings estimates (stdev_est) scaled by mean earnings estimate.	Diether, Malloy and Scherbina (2002)
Frontier	Efficient frontier index	Accounting	Frontier is the residual of a regression of log(BM) on log(book equity (ceq)), long-term debt (dltt) to assets (at), capital expenditures (capx) to revenue (sale), R&D expense (xrd) to revenue, advertising expense (xad) to revenue, property plant and equipment (ppent) to assets, EBIT (ebitda) to assets, and dummies for Fama-French's 48 industry definitions. Regression is updated each month with a rolling window of 60 months.	Nguyen and Swanson (2009)
GP	gross profits / total assets	Accounting	Revenue (sale) - cost of goods solds (cogs), divided by total assets (at). Drop if financial.	Novy-Marx (2013)
Governance	Governance Index	Other	Index available from http://faculty.som.yale.edu/andrewmetrick/data.html . The index is only available every 2-3 years for each firm, we replace intermediate missing values with the latest available one. Value-weighted.	Gompers, Ishii and Metrick (2003)
GrAdExp	Growth in advertising expenses	Accounting	Log of advertising expense (xad) minus log of advertising expense last year. Exclude if price less than 5, xad less than .1 or stock in the lowest decile of market value of equity.	Lou (2014)
GrLTNOA	Growth in long term operating assets	Accounting	Annual growth in net operating assets, minus accruals. Net operating assets are (rect + invt + ppent + aco + intan + ao- ap- lco- lo) / at. Accruals are (rect-l12.rect + invt - l12.invt + aco - l12.aco - (ap - l12.ap + lco - l12.lco) - dp) / ((at + l12.at)/2)	Fairfield, Whisenant and Yohn (2003)
GrSaleToGrInv	Sales growth over inventory growth	Accounting	Percentage growth in sales (sale) relative to average sales of t-1 and t-2, minus percentage growth in inventory (invt) relative to average inventory of t-1 and t-2. Both growth terms are calculated relative to t-1 only if t-2 is missing.	Abarbanell and Bushee (1998)
GrSaleToGrOverhead	Sales growth over overhead growth	Accounting	GrSaleToGrOverHead = Percentage growth in sales (sale) relative to average sales of t-1 and t-2, minus percentage growth in administrative expenses (xsga) relative to average administrative expenses of t-1 and t-2. Both growth terms are calculated relative to t-1 only if t-2 is missing.	Abarbanell and Bushee (1998)
Herf	Industry concentration (sales)	Other	Three-year rolling average of the three digit industry Herfindahl index based on firm revenue (sale). Exclude regulated industries (4011, 4210, 4213 & year $\leq$ 1980; 4512 & year $\leq$ 1978, 4812, 4813 & year $\leq$ 1982, 4900-4999 in any year)	Hou and Robinson (2006)
HerfAsset	Industry concentration (assets)	Other	Three-year rolling average of the three digit industry Herfindahl index based on firm assets (at). Exclude regulated industries (4011, 4210, 4213 & year $\leq$ 1980; 4512 & year $\leq$ 1978, 4812, 4813 & year $\leq$ 1982, 4900-4999 in any year)	Hou and Robinson (2006)
HerfBE	Industry concentration (equity)	Other	Three-year rolling average of the three digit industry Herfindahl index based on firm book equity. Exclude regulated industries (4011, 4210, 4213 & year $\leq$ 1980; 4512 & year $\leq$ 1978, 4812, 4813 & year $\leq$ 1982, 4900-4999 in any year)	Hou and Robinson (2006)
High52	52 week high	Price	Price (prc/cfacshr) divided by the maximum price over the previous 12 months.	George and Hwang (2004)
IO_ShortInterest	Inst own among high short interest	13F	Exclude all stocks with short interest (ShortInterest) below 99th percentile. IO_ShortInterest is institutional ownership (instown_perc). Keep NYSE Only.	Asquith Pathak and Ritter (2005)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
IdioVol3F	Idiosyncratic risk (3 factor)	Price	Standard deviation of residuals from Fama-French three factor regressions using the past month of daily data. Value weighted	Ang et al. (2006)
IdioVolAHT	Idiosyncratic risk (AHT)	Price	Standard deviation of residuals from CAPM regressions using the past year of daily data. Require at least 100 non-missing observations.	Ali, Hwang, and Trombley (2003)
Illiquidity	Amihud's illiquidity	Trading	Past twelve month average of: daily return (abs(ret)) divided by turnover((abs(prc)*vol)	Amihud (2002)
IndIPO	Initial Public Offerings	Event	1 if IPO in the past 6-36 months. 0 otherwise. IPO dates are taken from Jay Ritter's IPO data available at: http://bear.warrington.ufl.edu/ritter/ipodata.htm. Missing IPO dates imply IndIPO = 0	Ritter (1991)
IndMom	Industry Momentum	Price	Weighted average of firm-level 6 month buy-and-hold return. Average is taken over two digit industries each month and weights are based on market value of equity.	Grinblatt and Moskowitz (1999)
IndRetBig	Industry return of big firms	Price	Average monthly return (ret) of the 30% largest companies by market value of equity in the same Fama-French 48 industry. Exclude the largest 30% of companies for IndRetBig (not to compute the anomaly!)	Hou (2007)
IntMom	Intermediate Momentum	Price	Stock return between months t-12 and t-6	Novy-Marx (2012)
IntanBM	Intangible return using BM	Accounting	In each month, run a cross-sectional regression of a firm's five-year stock return on 5 year lagged BM (defined in Chen and Zimmermann (2022)) and a constructed regressor that is the change in BM from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanBM.	Daniel and Titman (2006)
IntanCFP	Intangible return using CFtoP	Accounting	In each month, run a cross-sectional regression of a firm's five-year stock return on the 5 year lagged CFP = (net income (ni) plus depreciation (dp))/market value of equity and a constructed regressor that is the change in CFP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanCFP.	Daniel and Titman (2006)
IntanEP	Intangible return using EP	Accounting	In each month, run a cross-sectional regression of a firm's five-year stock return on the 5 year lagged EP = net income (ni)/market value of equity and a constructed regressor that is the change in EP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanEP.	Daniel and Titman (2006)
IntanSP	Intangible return using Sale2P	Accounting	In each month, run a cross-sectional regression of a firm's five-year stock return on 5 year lagged SP (defined separately) and a constructed regressor that is the change in SP from 5 years ago to today plus the five-year stock return. The residual from that regression is IntanSP.	Daniel and Titman (2006)
InvGrowth	Inventory Growth	Accounting	Deflate invt growth using gnp deflator. Signal is deflated invt growth rate from fiscal year t to fiscal year t-1. Drop if 1 digit sic code is 4 or 6, or if at or ppent <= 0	Belo and Lin (2012)
InvestPPEInv	change in ppe and inv/assets	Accounting	One-year change in property, plants and equipment (ppegt) plus one year change in inventory (invt), scaled by one-year lagged assets (at).	Lyandres, Sun and Zhang (2008)
Investment	Investment to revenue	Accounting	Ratio of capital investment (capx) to revenue (revt) divided by the firm-specific 36-month rolling mean of that ratio. Exclude if revenue less than $10m.	Titman, Wei and Xie (2004)
LRreversal	Long-run reversal	Price	Stock return between months t-36 and t-13.	De Bondt and Thaler (1985)
Leverage	Market leverage	Accounting	Total liabilities (lt) divided by market value of equity.	Bhandari (1988)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
MRreversal	Medium-run reversal	Price	Stock return between months t-18 and t-13.	De Bondt and Thaler (1985)
MS	Mohanram G-score	Accounting	See code for details. MS is only evaluated for low BM firms and comes from combining three signals related to profitability and cash flow, two signals related to income volatility, and three signals related to investment.	Mohanram (2005)
MaxRet	Maximum return over month	Price	Maximum of daily returns (ret) over the previous month	Bali, Cakici, and Whitelaw (2011)
MeanRankRevGrowth	Revenue Growth Rank	Accounting	Rank firms by their annual revenue growth each year over the past 5 years. MeanRankRevGrowth is the weighted average of ranks over the past 5 years, that is, MeanRankRevGrowth = (5*Rank$_{t-1}$ + 4*Rank$_{t-2}$ + 3*Rank$_{t-3}$ + 2*Rank$_{t-4}$ + 1*Rank$_{t-5}$)/15. Exclude NASDAQ stocks.	Lakonishok, Shleifer and Vishny (1994)
Mom12m	Momentum (12 month)	Price	Stock return between months t-12 and t-1	Jegadeesh and Titman (1993)
Mom12mOffSeason	Momentum without the seasonal part	Price	Average return in other months over the previous year.	Heston and Sadka (2008)
Mom6m	Momentum (6 month)	Price	Stock return between months t-6 and t-1	Jegadeesh and Titman (1993)
Mom6mJunk	Junk Stock Momentum	Price	Mom6m. Include only stocks with a credit rating (splticrm) of BBB or lower. Drop if missing credit rating or non-standard credit rating.	Avramov et al (2007)
MomOffSeason	Off season long-term reversal	Price	Average return in other months over the preceding 2-5 years.	Heston and Sadka (2008)
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Price	Average return in other months over the preceding 6-10 years.	Heston and Sadka (2008)
MomOffSeason11YrPlus	Off season reversal years 11 to 15	Price	Average return in other months over the preceding 11-15 years.	Heston and Sadka (2008)
MomOffSeason16YrPlus	Off season reversal years 16 to 20	Price	Average return in other months over the preceding 16-20 years.	Heston and Sadka (2008)
MomRev	Momentum and LT Reversal	Price	Binary variable equal to 1 if firm is in the highest Mom6m quintile and the lowest Mom36m quintile, and equal to 0 if firm is in the lowest Mom6m quintile and the highest Mom36m quintile. Exclude if price less than 5.	Chan and Ko (2006)
MomSeason	Return seasonality years 2 to 5	Price	Average return in the same month over the preceding 2-5 years.	Heston and Sadka (2008)
MomSeason06YrPlus	Return seasonality years 6 to 10	Price	Average return in the same month over the preceding 6-10 years.	Heston and Sadka (2008)
MomSeason11YrPlus	Return seasonality years 11 to 15	Price	Average return in the same month over the preceding 11-15 years.	Heston and Sadka (2008)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
MomSeason-16YrPlus	Return seasonality years 16 to 20	Price	Average return in the same month over the preceding 16-20 years.	Heston and Sadka (2008)
MomSeasonShort	Return seasonality last year	Price	Average return in the same month in the previous year.	Heston and Sadka (2008)
MomVol	Momentum in high volume stocks	Price	Define momentum as Mom6m, and volume as the rolling average of the past 6 months of monthly turnover (minimum 5 months). Independent sort stocks into 10 momentum ports and 3 volume ports. Keep if volume is in the top port, and assign signal = momentum port. Drop if less than 2 years on CRSP.	Lee and Swaminathan (2000)
NOA	Net Operating Assets	Accounting	Difference between operating assets and operating liabilities, scaled by lagged total assets. Operating assets are total assets (at) minus cash- and short-term investments (che), operating liabilities are total assets minus long-term debt (dltt), minority interest (mib), deferred charges (dc) and book equity (ceq).	Hirshleifer et al. (2004)
NetDebtFinance	Net debt financing	Accounting	Long-term debt issuance (dltis) minus long-term debt reduction (dltr) minus current debt changes (dlcch), scaled by average total assets (at) in years t-1 and t. Replace missing values of dlcch with 0. Exclude if ratio is greater than 1.	Bradshaw, Richardson and Sloan (2006)
NetDebtPrice	Net debt to price	Accounting	Long-term debt (dltt) plus debt in current liabilities (dlc) plus preferred stock (pstk) plus preferred dividends in arrears (dvpa) minus treasury stock (tstkp) minus cash and short-term investments (che), scaled by market value of equity. Exclude if SIC between 6000 and 6999, or if missing value for total assets (at), net income (ib), common shares outstanding (csho), book value of equity (ceq) or price close fiscal year (prcc_f). Keep only 3rd B/M Quintile, following Table 4 (and in contrast to Table 1).	Penman, Richardson and Tuna (2007)
NetEquityFinance	Net equity financing	Accounting	Sale of common stock (sstk) minus purchase of common stock (prstkc), scaled by average total assets (at) from years t and t-1. Exclude if absolute value of ratio is greater than 1.	Bradshaw, Richardson and Sloan (2006)
NetPayoutYield	Net Payout Yield	Accounting	Dividends (dvc) plus purchase of common and preferred stock (prstkc) minus sale of common and preferred stock (sstk), divided by market value of equity lagged 6 months. Exclude if NetPayoutYield is 0, financial firm based on SIC code, ceq <= 0, or less than 2 years in CRSP	Boudoukh et al. (2007)
NumEarnIncrease	Earnings streak length	Accounting	Number if consecutive 4-quarter increases in ibq, up to 8.	Loh and Warachka (2012)
OPLeverage	Operating leverage	Accounting	Sum of administrative expenses (xsga) and cost of goods sold (cogs), scaled by total assets (at). Use xsga = 0 if xsga is missing.	Novy-Marx (2011)
OScore	O Score	Accounting	OScore = -1.32 - .407*log(at/GNP deflator) + 6.03*(lt/at) - 1.43*((act - lct)/at) + .076*(lct/act) - 1.72*I(lt > at) - 2.37*(ib/at) - 1.83*(fopt/lt) + .285*(ib + ib_{t-12} + ib_{t-24} < 0) - .521*((ib - ib_{t-12})/(abs(ib) + abs(ib_{t-12}))). fopt = oancf if fopt is missing. Exclude if SIC code between 3999 and 4999, or greater than 5999. Exclude if price less than 5. Then exclude if OScore is in bottom quintile of OScore (original paper shows non-monotonic returns, as does our replication)	Dichev (1998)
OperProf	operating profits / book equity	Accounting	Revenue (revt) minus cost (cogs) - administrative expenses (xsga) - interest expenses (xint), scaled by book value of equity (ceq). Exclude smallest size tercile.	Fama and French (2006)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
OperProfRD	Operating profitability R&D adjusted	Accounting	Revenue (revt) minus cost (cogs) - (administrative expenses (xsga) - R&D expenses (xrd)), all divided by total assets (at) in year t. Replace all variables in the numerator with 0 if they are missing. Exclude if share code is greater 11, market value of equity, BM or total assets are missing, or if SIC code between 6000 and 6999.	Ball et al. (2016)
OptionVolume1	Option to stock volume	Options	Total monthly option volume (volume) over all puts and calls, divided by monthly stock trading volume (vol). Exclude if price less than 1 or share code greater 11 or option volume or stock volume data are missing for the previous month.	Johnson and So (2012)
OptionVolume2	Option volume to average	Options	Based off of OptionVolume1. OptionVolume2 = OptionVolume1 / average of OptionVolume1 from months t-6 to t-1.	Johnson and So (2012)
OrderBacklog	Order backlog	Accounting	Order backlog (ob) divided by average total assets (at) in years t-1 and t. Exclude if order backlog is 0.	Rajgopal, Shevlin, Venkatachalam (2003)
OrgCap	Organizational capital	Accounting	Defined recursively. Set xsga to 0 if missing. Initialize with OrgCap = 4*general expenses (xsga) in the first year, and calculate as .85*OrgCap previous year + xsga/gnpdeflator current year thereafter. Scale by total assets (at). Keep only december year ends, and non-financials, and non-missing sic code. Then winsorize at the 1% level and standardized by subtracting the same month within-industry mean (Fama French 17 industries) and dividing by the same month within industry standard deviation of OrgCap.	Eisfeldt and Papanikolaou (2013)
PS	Piotroski F-score	Accounting	Sum of nine indicator variables which are: 1 if net income (ib) greater 0; 1 if net cash flow (oancf) greater 0; 1 if return on assets (ib/at) increased relative to previous year; 1 if net cash flow greater net income; 1 if long-term debt to assets (dltt/at) declined over the previous year; if current assets to current liabilities (act/lct) increased over the previous year; 1 if ebit/sale (ebit = ib + txt + xint) increased over the previous year; 1 if revenue to assets increased over the previous year; 1 if shrout $\leq$ shrout last year. Include highest quintile of book-to-market only. Exclude if missing any of the input variables.	Piotroski (2000)
PatentsRD	Patents to RD expenses	Other	Drop obs before 1975. Set expenses for research and development (xrd) and number of patents (npat) to 0 if missing. Calculate Patents to RD as patents in a year divided by $xrd_{t-2} + .8xrd_{t-3} + .6xrd_{t-4} + .4xrd_{t-5} + .2xrd_{t-6}$. Drop if denominator = 0, 2 years or less in Compustat, sic in 6000s, ceq < 0. Double independent sort using (a) size NYSE median (b) terciles of Patents to RD. Long if in small size, highest tercile of Patents to RD, short if in small size, smallest tercile.	Hirschleifer, Hsu and Li (2013)
PayoutYield	Payout Yield	Accounting	Sum of dividends (dvc), purchase of common and preferred stock (prstkc) and max(preferred stock redemption value (pstkrv), 0) over market value of equity lagged 6 months. Exclude if PayoutYield $\leq$ 0, financial firm based on SIC code, ceq <= 0, or less than 2 years in CRSP	Boudoukh et al. (2007)
PctAcc	Percent Operating Accruals	Accounting	Income before extraordinary items (ib) minus net cash flow (oancf) divided by absolute value of ib. If oancf is missing, PctAcc is defined as ((act - act_{t-12}) - (che - che_{t-12}) - ((lct - lct_{t-12}) - (dlc - dlc_{t-12}) - (txp - txp_{t-12}) - dp))/abs(ib). In either case, if ib is equal to 0, divide by .01 instead. Exclude if price less than 5.	Hafzalla, Lundholm, Van Winkle (2011)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
PctTotAcc	Percent Total Accruals	Accounting	Net income (ni) minus (purchase of common and preferred stock (prstkcc) minus sale of common and preferred stock (sstk) plus dividends (dvt), cash flow from operations (oancf), from financing (fincf) and investment (ivncf)). Scaled by absolute value of net income.	Hafzalla, Lundholm, Van Winkle (2011)
PredictedFE	Predicted Analyst forecast error	Accounting	The fitted value from cross-sectional regressions of analyst earnings' forecast errors on cross-sectional rankings of 5-year sales growth, book-to-market, AOP, and analyst long term growth. See code for details.	Frankel and Lee (1998)
Price	Price	Price	Log of absolute value of price (prc).	Blume and Husic (1973)
PriceDelayRsq	Price delay r square	Price	Each July regress stock return on day t on market return in $t, t-1, \ldots, t-4$ using observations from July 1 of the previous year to June 30 of the current year. Then regress again with no market return lags. PriceDelayRsq = 1 - [Rsq from second regression]/[Rsq from first regression]	Hou and Moskowitz (2005)
PriceDelaySlope	Price delay coeff	Price	Each July regress daily stock return (ret) on market return (mktrf) in $t, t-1, \ldots, t-4$ with observations over the previous year. Define PriceDelaySlope as the ratio of 1*beta on $\text{mktrf}_t - 1$ + 2*beta on $\text{mktrf}_t - 2$ + 3*beta on $\text{mktrf}_t - 3$ + 4*beta on $\text{mktrf}_t - 4$], and [beta on mktrf_t + beta on $\text{mktrf}_t - 1$ + beta on $\text{mktrf}_t - 2$ + beta on $\text{mktrf}_t - 3$ + beta on $\text{mktrf}_t - 4$].	Hou and Moskowitz (2005)
PriceDelayTstat	Price delay SE adjusted	Price	Each July regress daily stock return (ret) on market return (mktrf) in $t, t-1, \ldots, t-4$ using observations from July 1 of the previous year to June 30 of the current year. Trim the highest and lowest 1% of estimated coefficients, standard errors, and t-stats. Define PriceDelayTstat as the ratio of [1*tstat on $\text{mktrf}_t - 1$ + 2*tstat on $\text{mktrf}_t - 2$ + 3*tstat on $\text{mktrf}_t - 3$ + 4*tstat on $\text{mktrf}_t - 4$], and [tstat on mktrf_t + tstat on $\text{mktrf}_t - 1$ + tstat on $\text{mktrf}_t - 2$ + tstat on $\text{mktrf}_t - 3$ + tstat on $\text{mktrf}_t - 4$]. Finally winsor the extreme 10 and 90 percentiles each month.	Hou and Moskowitz (2005)
ProbInformed-Trading	Probability of Informed Trading	Trading	Download parameter estimates from the page for Duarte, Hu, Young, JFE 2020 https://edwinhu.github.io/pin/ and apply Easley et al's Equation 5. Use Year t PIN estimates to forecast returns throughout Year t+1	Easley, Hvidkjaer and O'Hara (2002)
RD	R&D over market cap	Accounting	R&D expense (xrd) over market value of equity.	Chan, Lakonishok and Sougiannis (2001)
RDAbility	R&D ability	Accounting	Regress log of sales growth (sale over sale in previous year) on log of (1+ xrd/sale) in 5 bivariate regressions with (1+xrd/sale) lagged by $1, \ldots, 5$ years. Run regressions over previous 8 years and require at least 6 non-missing observations. Also require at least half of past research and development observations to be non-zero. RDAbility is the mean of the coefficients on the five lags of log(1+xrd/sale). Set to missing if firm is not in the highest tercile of xrd/sale in a year or if research and development expenses are non-positive.	Cohen, Diether and Malloy (2013)
RDIPO	IPO and no R&D spending	Event	Binary variable equal to 1 if R&D expense (xrd) = 0 and IndIPO = 1. 0 otherwise.	Guo, Lev and Shi (2006)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
RDS	Real dirty surplus	Accounting	Define Dirty Surplus as annual change in marketable securities adjustment msa plus annual change in retained earnings adjustment (recta) + .65 times the annual change in min(Unrecognized prior service cost (pcupsu) - Pension additional minimum liability (paddml),0). Real dirty surplus is the annual change in book equity (ceq) minus dirty surplus minus (net income (ni) minus dividends preferred (dvp)) + dividends (divamt) - end-of-fiscal-year-stock-price (prcc_f)*annual change in common shares outstanding (csho).	Landsman et al. (2011)
RDcap	R&D capital-to-assets	Accounting	R&D capital to assets is the weighted sum of lagged R&D expenditures scaled by the assets (at). We replace xrd with 0 if xrd is missing and compute the numerator as $xrd_t + .8xrd_{t-1} + .6xrd_{t-2} + .4xrd_{t-3} + .2xrd_{t-4}$. Replace RDcap with missing before 1980 or if firm is in upper two thirds of market cap (shrout*abs(prc)) distribution in a month.	Li (2011)
REV6	Earnings forecast revisions	Analyst	Define revisions as the change in the mean earnings estimate (meanest) for the next quarter from month t-1 to t, scaled by stock price in month t-1. REV6 is the sum of that variable from months t-6 to t.	Chan, Jegadeesh and Lakonishok (1996)
RIO_Disp	Inst Own and Forecast Dispersion	13F	Follow RIO_MB, except define Disp as the stdev of IBES forecasts where fpi == 1 divided by at, and sort on Disp instead of MB. Finally, let RIO_Disp = lagged RIO quintile if the Disp quintile >= 4.	Nagel (2005)
RIO_MB	Inst Own and Market to Book	13F	Residual institutional ownership (RIO) is defined as log(institutional ownership (instown_perc)/(1-institutional ownership)) + 23.6 - 2.89*log(market value of equity) +.08*log(market value of equity)^2. Replace instown_perc with 0 if it is missing, with .9999 if it's above .9999, and with .0001 if it's below .0001. Then lag RIO by 6 months. Keep only stocks with size > 20th percentile across exchcd == 1 or 2. Define MB as market cap / (ceq + txditc), where txditc = 0 if missing, and MB is replaced with missing if ceq < 0. Then sort into quintiles based on the lagged RIO, and sort into quintiles based on MB. Finally, let RIO_MB = lagged RIO quintile if the MB quintile = 5.	Nagel (2005)
RIO_Turnover	Inst Own and Turnover	13F	Follow RIO_MB, except define turnover as vol/shrout. Let RIO_Turnover = lagged RIO quintile if the Volatility quintile == 5	Nagel (2005)
RIO_Volatility	Inst Own and Idio Vol	13F	Follow RIO_MB, except define volatility as the rolling standard deviation of the last 12 months of the stock return. Let RIO_Disp = lagged RIO quintile if the Volatility quintile == 5	Nagel (2005)
RIVolSpread	Realized minus Implied Vol	Options	Realized Vol (past 30 days) minus ATM Implied Vol	Bali and Hovakimian (2009)
RealizedVol	Realized (Total) Volatility	Price	Standard deviation of residuals from CAPM regressions using the past month of daily data. Value weighted	Ang et al. (2006)
Recomm_ShortInterest	Analyst Recommendations and Short-Interest	Analyst	Go long firms in lowest quintile of short interest (shortint/shrout) and lowest quintile of analyst recommendations (monthly consensus recommendation using the most recent analyst recommendation in the past 12 months). Go short firms in highest quintile of short interest and highest quintile of analyst recommendations.	Drake, Rees and Swanson (2011)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
Residual-Momentum	Momentum based on FF3 residuals	Price	Run a rolling regression over 36 months of excess return (retrf) on excess market return (mktrf), size and value factors (smb, hml) and compute idiosyncratic returns as the one-month lagged residual. ResidualMomentum is the rolling mean of the residual divided by the rolling standard deviation of the residual, both computed over the past 11 months.	Blitz, Huij and Martens (2011)
ReturnSkew	Return skewness	Price	Skewness of daily returns (ret) over previous month.	Bali, Engle and Murray (2015)
ReturnSkew3F	Idiosyncratic skewness (3F model)	Price	Skewness of idiosyncratic returns computed as residuals from regression of daily excess returns (ret - rf) on Fama-French factors (mktrf, smb, hml) over the previous month. We require at least 15 non-missing observations.	Bali, Engle and Murray (2015)
RevenueSurprise	Revenue Surprise	Accounting	Define revenue per share as quarterly revenue (revtq) divided by quarterly common shares outstanding (cshprq). RevenueSurprise is the 4-quarter change in revenue per share minus the average 4-quarter change in revenue per share over the previous 2 years. RevenueSurprise is scaled by its standard deviation over the previous 2 years. Exclude if price less than 5.	Jegadeesh and Livnat (2006)
RoE	net income / book equity	Accounting	Net income (ni) over book value of equity (ceq). Exclude if price less than 5.	Haugen and Baker (1996)
SP	Sales-to-price	Accounting	Ratio of annual sales (sale) to market value of equity.	Barbee, Mukherji and Raines (1996)
STreversal	Short term reversal	Price	Stock return (ret) over the previous month.	Jegadeesh (1990)
ShareIss1Y	Share issuance (1 year)	Accounting	Growth in number of shares between t-18 and t-6. Number of shares is calculated as shrout/cfacshr to adjust for splits.	Pontiff and Woodgate (2008)
ShareIss5Y	Share issuance (5 year)	Accounting	5-year growth in number of shares. Number of shares is calculated as shrout/cfacshr to adjust for splits.	Daniel and Titman (2006)
ShareRepurchase	Share repurchases	Accounting	Binary variable equal to 1 if stock repurchase indicated in cash flow statement (prstkc $>$ 0), and 0 if prstkc $=$ 0.	Ikenberry, Lakonishok and Vermaelen (1995)
ShareVol	Share Volume	Trading	Let tempvol $=$ sum of monthly share trading volume (vol) over the previous three months, scaled by 3 times common shares outstanding (shrout). Let ShareVol $=$ 1 if tempvol $>$ 10%, and ShareVol $=$ 0 if tempvol $<$ 5%.	Datar, Naik and Radcliffe (1998)
ShortInterest	Short Interest	Trading	Short-interest from Compustat (shortint) scaled by shares outstanding (shrout). Short-interest data are available bi-weekly with a four day lag. We use the mid-month observation to make sure data would be available in real time.	Dechow et al. (2001)
Size	Size	Price	Log of monthly market value of equity (abs(prc)*shrout)).	Banz (1981)
SmileSlope	Put volatility minus call volatility	Options	Using OptionMetrics's daily volatility surfaces (vsurfd), keep last observation each month, delta $=$ 0.50 or -0.50, and days to expiration $=$ 30. The signal is then the difference between put implied vol and call implied vol.	Yan (2011)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
Spinoff	Spinoffs	Event	Spinoffs are identified as all observations in the CRSP acquisition file with valid acperm entry. Spinoff is a binary variable equal to 1 if a firm is identified in the CRSP Acquisition data and if it has at most two years of history in the CRSP stock return data. Spinoff is equal to 0 otherwise.	Cusatis, Miles and Woolridge (1993)
SurpriseRD	Unexpected R&D increase	Accounting	Binary variable equal to 1 if: R&D (xrd) scaled by revenue (revt) is positive, R&D scaled by total assets (at) is positive, annual R&D growth is greater than 5%, annual growth in R&D over total assets is greater than 5%. SurpriseRD is 0 otherwise.	Eberhart, Maxwell and Siddique (2004)
Tax	Taxable income to income	Accounting	Ratio of Taxes paid and tax share of net income. Numerator is defined as the sum of foreign (txfo) and federal (txfed) income taxes. If either one is missing, numerator is defined as total taxes (txt) minus deferred taxes (txdi). Denominator is the product of the prevailing tax rate and net income (ib). Tax rate is .48 before 1979, .46 from 1979 to 1986, .4 in 1987, .34 between 1988 and 1992 and .35 from 1993 onwards. If net income is negative, and the numerator is positive, tax is defined as 1. Exclude if price less than 5.	Lev and Nissim (2004)
TotalAccruals	Total accruals	Accounting	Before 1988: Change in net working capital ((act - che) - (lct - dlc)) plus change in net noncurrent assets ((at - act - ivao) - (lt - dlc - dltt)) plus change in net financial assets ((ivst + ivao - (dltt + dlc + pstk)). Starting in 1988: net income (ni) minus total, operating and investment cashflows (oancf, ivncf, fincf) plus stock sales minus repurchases and dividends (sstk, prstkc, dv)). Scaled by lagged total assets (at). Replace missings in ivao, ivst, dltt, dlc, pstk sstk, prstkc, dv with 0.	Richardson et al. (2005)
TrendFactor	Trend Factor	Price	See paper section 2.1 and 2.2	Han, Zhou and Zhu (2016)
UpRecomm	Up Forecast	Analyst	Keep fpi = 1. Binary variable equal to 1 if mean earnings forecast (meanest) decreased over the past month.	Barber et al. (2001)
VarCF	Cash-flow to price variance	Accounting	Rolling variance of (ib+dp)/mve_c over the past 60 months (minimum 24 months data required).	Haugen and Baker (1996)
VolMkt	Volume to market equity	Trading	Average monthly dollar trading volume (vol*abs(prc)) over the previous 12 months, scaled by market value of equity. Exclude if price less than 5.	Haugen and Baker (1996)
VolSD	Volume Variance	Trading	Rolling standard deviation of monthly trading volume (vol) over the past 36 months (require at least 24 observations). Include only NYSE stocks.	Chordia, Subrahmanyam and Anshuman (2001)
VolumeTrend	Volume Trend	Trading	Rolling coefficient from regressing monthly trading volume on a linear time trend over a window of 60 months (require that at least 30 exist). Scale coefficient by 60-month average of trading volume.	Haugen and Baker (1996)
XFIN	Net external financing	Accounting	Sale of common stock (sstk) minus dividends (dv) minus purchase of common stock (prstkc) plus long-term debt issuance (dltis) minus long-term debt reductions (dltr). Scaled by total assets (at).	Bradshaw, Richardson and Sloan (2006)
betaVIX	Systematic volatility	Price	Coefficient on daily change in the VIX of a 1-month rolling window regression of daily stock excess returns on market return and the daily change in the CBOE S&P 100 volatility index (downloaded from FRED). Require at least 15 non-missing observations.	Ang et al. (2006)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
cfp	Operating Cash flows to price	Accounting	Operating cash-flow (oancf) divided by market value of equity. If operating cash-flow is missing, replace by difference betwee net income (ib) and level of accruals, where the latter is the annual change in current assets (act) minus the annual change in cash and short-term investments (che), minus the annual change in current liabilities (lct) plus the annual change in debt in current liabilities (dlc) plus the annual change in payable income taxes (txp) plus depreciation (dp).	Desai, Rajgopal, Venkatachalam (2004)
dCPVolSpread	Change in put vol minus change in call vol	Options	Take difference of dVolCall and dVolPut	An, Ang, Bali and Cakici (2014)
dNoa	change in net operating assets	Accounting	12-month growth in Net Operating Assets scaled by lagged total assets (at). Net Operating assets are operating assets minus operating liabilities. Operating assets are total assets (at) minus cash- and short-term investments (che), operating liabilities are total assets minus long-term debt (dltt), minority interest (mib), deferred charges (dlc), book equity (ceq) and preferred stock (pstk), all items (except at and ceq) replaced with 0 if missing.	Hirshleifer, Hou, Teoh, Zhang (2004)
dVolCall	Change in call vol	Options	Using OptionM vol surface, 30 day mat, delta = 0.5, find first diff of implied vol	An, Ang, Bali and Cakici (2014)
dVolPut	Change in put vol	Options	Using OptionM vol surface, 30 day mat, delta = 0.5, find first diff of implied vol	An, Ang, Bali and Cakici (2014)
fgr5yrLag	Long-term EPS forecast	Analyst	Lag long-term earnings forecast (fgr5yr) by 6 months. Then keep only June observations, and fill in missing with most recent obs. Exclude if book equity (ceq), net income (ib), deferred taxes (txdi), dividends (dvp), revenue (sale) or depreciation (dp) is missing.	La Porta (1996)
grcapx	Change in capex (two years)	Accounting	Growth rate of capital expenditures (capx) relative to two years ago. If capx is missing, replace with annual change in property, plant and equipment (ppent).	Anderson and Garcia-Feijoo (2006)
grcapx3y	Change in capex (three years)	Accounting	Capital expenditures (capx) divided by the sum of capital expenditures from year - 1, year -2, and year -3. If capx is missing, replace with annual change in property, plant and equipment (ppent).	Anderson and Garcia-Feijoo (2006)
hire	Employment growth	Other	Change in number of employees (emp) between t -1 and t, scaled by average number of employees in t-1 and t. Replace hire with 0 if emp or lagged emp is missing.	Bazdresch, Belo and Lin (2014)
iomom_cust	Customers momentum	Other	We download BEA Make-Use Tables, match to Compustat by NAICS assuming 5 year lag, compute returns within BEA 70 industries. Then match each industry-year to matched-industry weights corresponding to IO tables as follows: for supplier mom, industry comes from cols of Use table, matched industries from the rows. For customer mom: industry from rows of make table, matched industries from cols. Weights exclude own-industry entries. For each industry-month, average returns of matched industries, weighted using IO tables. Sort industries into deciles based on matched returns, assign firm-months to industry deciles, Finally, long stocks in deciles 8-10 and short decile 1. Drop pre-1986 due to NAICS availability.	Menzly and Ozbas (2010)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
iomom_supp	Suppliers momentum	Other	We download BEA Make-Use Tables, match to Compustat by NAICS assuming 5 year lag, compute returns within BEA 70 industries. Then match each industry-year to matched-industry weights corresponding to IO tables as follows: for supplier mom, industry comes from cols of Use table, matched industries from the rows. For customer mom: industry from rows of make table, matched industries from cols. Weights exclude own-industry entries. For each industry-month, average returns of matched industries, weighted using IO tables. Sort industries into deciles based on matched returns, assign firm-months to industry deciles, Finally, long stocks in deciles 8-10 and short decile 1. Drop pre-1986 due to NAICS availability.	Menzly and Ozbas (2010)
realestate	Real estate holdings	Accounting	Industry-adjusted value of real estate holdings. Real estate holdings are (fatb+fatl)/ppegt if available, and (ppenb+ppenl)/ppent otherwise. Drop firms in 2 digit sics with < 5 firm or missing at or missing both ppent and ppegt. Subtract monthly industry-mean at the 2 digit SIC level.	Tuzel (2010)
retConglomerate	Conglomerate return	Price	Identify conglomerate firms as those with multiple OPSEG or BUSSEG entries in the Compustat segment data (and require that at least 80% of firm's total assets are covered by segment data). Compute monthly stock return at the 2-digit SIC level for stand-alone (non-conglomerate) firms only, and match those returns to conglomerates' segments. Compute weighted conglomerate return as the industry return of stand-alone companies, weighted with a conglomerate's total sales in each industry.	Cohen and Lou (2012)
roaq	Return on assets (qtrly)	Accounting	Quarterly net income (ibq) divided by lagged total assets (atq).	Balakrishnan, Bartov and Faurel (2010)
sfe	Earnings Forecast to price	Analyst	Median estimate for next year eps (fpi = 1) in March, divided by stock price from December. Dec fiscal year ends only, keep only forecasts more than 90 days out. Keep only below median analyst coverage each month.	Elgers, Lo and Pfeiffer (2001)
sinAlgo	Sin Stock (selection criteria)	Other	Using Compustat Segment data, sinAlgo is defined as a binary variable equal to 1 if at least one segment of a firm is listed as being in at least one of the following industries: sic $\geq$ 2100 & sic $\leq$ 2199, sic $\geq$2080 & sic $\leq$ 2085, NAICS in {7132, 71312, 713210, 71329, 713290, 72112, 721120}. As in the original paper, we assume that the sin stock indicator applies to the entire history and future of the identified firm. sinAlgo is equal to 0 if the firm is not identified in the CS Segment data as a sin stock and if the firm is in one of the following industries: (sic $\geq$ 2000 & sic $\leq$ 2046) OR (sic $\geq$ 2050 & sic $\leq$ 2063) OR (sic $\geq$ 2070 & sic $\leq$ 2079) OR (sic $\geq$ 2090 & sic $\leq$ 2092) OR (sic $\geq$ 2095 & sic $\leq$ 2099) OR (sic $\geq$ 2064 & sic $\leq$ 2068) OR (sic $\geq$ 2086 & sic $\leq$ 2087) OR (sic $\geq$ 920 & sic $\leq$ 999) OR (sic $\geq$ 3650 & sic $\leq$ 3652) OR sic == 3732 OR (sic $\geq$ 3931 & sic $\leq$ 3932) OR (sic $\geq$ 3940 & sic $\leq$ 3949) OR (sic $\geq$ 7800 & sic $\leq$ 7833) OR (sic $\geq$ 7840 & sic $\leq$ 7841) OR (sic $\geq$ 7900 & sic $\leq$ 7911) OR (sic $\geq$ 7920 & sic $\leq$ 7933) OR (sic $\geq$ 7940 & sic $\leq$ 7949) OR sic == 7980 OR (sic $\geq$ 7990 & sic $\leq$ 7999)	Hong and Kacperczyk (2009)
skew1	Volatility smirk near the money	Options	Using OptionMetrics data, among options with duration between 10 and 60 days, implied volatility of put option with moneyness closest to but above 1 minus implied volatility of call option with moneyness closest to but below 1. Keep only volume > 0, implied vol between 0.03 and 2.0, price > 0.125, open interest > 0.	Xing, Zhang and Zhao (2010)

Table IA.13: Stock Characteristics. Characteristics used to construct predictive signals.

Acronym	Characteristic	Category	Detailed Definition	Citation
std_turn	Share turnover volatility	Trading	Standard deviation of turnover (vol/shrout) over the past 36 months.	Chordia, Subrahmanyam and Anshuman (2001)
tang	Tangibility	Accounting	Cash and short-term investments (che) plus .715*receivables (rect) + .547*inventory (invt) + .535* property, plant and equipment (ppent), scaled by total assets (at). Only defined for manufacturing firms (SIC $\geq$ 2000 and SIC <4000). Exclude the lowest tercile of manufacturing firms by total assets.	Hahn and Lee (2009)
zerotrade12M	Days with zero trades	Trading	In each month, count the number of days with no trades. Define zerotrade as the number of days without trades plus (the sum of monthly turnover (vol/shrout) divided by $48*10^5$), multiplied by 21/number of trading days per month. Take 12-month average.	Liu (2006)
zerotrade1M	Days with zero trades	Trading	In each month, count the number of days with no trades. Define zerotrade as the number of days without trades plus (the sum of monthly turnover (vol/shrout) divided by $48*10^5$), multiplied by 21/number of trading days per month. Take 1-month average.	Liu (2006)
zerotrade6M	Days with zero trades	Trading	In each month, count the number of days with no trades. Define zerotrade as the number of days without trades plus (the sum of monthly turnover (vol/shrout) divided by $48*10^5$), multiplied by 21/number of trading days per month. Zerotrade is the 6-month average of that variable.	Liu (2006)

References in Internet Appendix

Chen, A. Y., & Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, *11*(02), 207–264.

Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *Journal of Finance*, *75*(1), 173–228.

Friedman, J., Hastie, T., Höfling, H., & Tibshirani, R. (2007). Pathwise coordinate optimization. *Annals of Applied Statistics*, *1*(2), 302–332.

Greene, W. H. (1981). Sample selection bias as a specification error: A comment. *Econometrica*, 795–798.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, *70*(3), 393–408.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of economic and social measurement* (pp. 475–492). NBER.

Hellwig, M. F. (1980). On the aggregation of information in competitive markets. *Journal of Economic Theory*, *22*(3), 477–498.

Lee, J. D., Sun, D. L., Sun, Y., & Taylor, J. E. (2016). Exact post-selection inference, with application to the lasso. *Annals of Statistics*, *44*(3), 907–927.

Linnainmaa, J. T. (2011). Why do (some) households trade so much? *Review of Financial Studies*, *24*(5), 1630–1666.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Sun, T., & Zhang, C.-H. (2012). Scaled sparse linear regression. *Biometrika*, *99*(4), 879–898.

Tibshirani, R. J. (2013). The lasso problem and uniqueness. *Electronic Journal of Statistics*, *7*, 1456–1490.

Xu, H., Caramanis, C., & Mannor, S. (2010). Robust regression and Lasso. *IEEE Transactions on Information Theory*, *56*(7), 3561–3574.