Learning-by-Doing in Predictive Signal Adoption

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Abstract

This paper uncovers behavioral frictions that impede statistical learning and limit investors' ability to exploit return predictability. Combining evidence from mutual fund portfolio holdings with controlled trading contests in which participants receive common predictor sets, I document substantial under-adoption of predictive signals. An investor's experience, rather than signal informativeness, is the primary determinant of signal adoption. Exploiting institutional features of the trading contests, I uncover a familiarity bias toward recognizable signals, and an aversion to specifying complex predictive models that diminishes with experience. Gains from return predictability thus concentrate among experienced investors, who converge in the models they specify.

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1 Introduction

Data-driven prediction is increasingly central to economic decision-making, and finance is a leading case. Academic researchers have uncovered an expanding set of return-predictive signals,[1] which become freely available to practitioners upon publication. Yet a number of studies find that institutional investors do not act upon these signals (Lewellen, 2011; Edelen, Ince, and Kadlec, 2016; McLean, Pontiff, and Reilly, 2025), despite the economic incentives to do so. One possibility is that behavioral frictions contribute to this puzzling reluctance. Recent experimental work has begun to examine how beliefs are influenced by the provision of a predictive signal (Andries, Bianchi, Huynh, and Pouget, 2025), but less is known about the mechanisms that shape investors' decisions to select among a variety of signals and incorporate them into a realistic trading strategy. Shedding light on this process bears directly on the nature and persistence of return predictability.

This paper uncovers behavioral frictions that impede investors' use of publicly available predictive signals, and shows that experience plays a role in overcoming them. I study two complementary settings. The first is a series of tightly controlled trading contests in which participants are endowed with common sets of predictive signals; this setting permits a clean analysis of behavioral mechanisms. I find that learning-by-doing (Arrow, 1962) drives the adoption of genuinely predictive signals: as investors gain experience, they become increasingly willing to adopt signals that are informative. Importantly, this mechanism is distinct from statistical learning from data, since investors endowed with exactly the same datasets (both in signal identities and number of observations) respond differently based on their experience. Novice investors default to adopting familiar signals regardless of their informativeness. Novices also demonstrate an aversion to specifying complex predictive models, which they overcome as they accumulate experience.

In my second, complementary setting, I analyze the portfolio decisions of mutual fund managers, and show a similar pattern holds: experience predicts the adoption of informative signals. By establishing the importance of behavioral frictions in the contest setting and finding parallels in the behavior of institutional investors, I argue that such frictions are an important part of the explanation for the limited adoption documented in prior work.

This paper begins by exploiting a series of online trading contests run by the Quantiacs platform to identify how investors use predictive signals. This first setting offers a controlled yet

[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).

realistic environment: 874 participants across 12 contests (launched during 2014–2019) implement futures trading strategies,[2] competing for profit-sharing contracts and being 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 institutional setting rules out a number of potential confounding factors, as I describe further in Section 2.1. Contestants develop their strategies using a backtest (in-sample) period and are then evaluated on their performance during a subsequent out-of-sample period. 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.

Among investors who take part in the same contest, and are thus constrained to make use of an identical shared dataset, additional 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 examine within-contest variation. Including additional investor fixed effects to control for unobserved heterogeneity such as skill further confirms that experience positively impacts both in-sample (backtest) and out-of-sample Sharpe Ratios (SRs). Taken together, the performance trajectories of contestants who take part in multiple trading contests reveal that accumulated experience enables investors to better exploit the historical data they are endowed with.

It is particularly striking that the experience gradient holds even within the same contest, where all contestants are endowed with identical datasets. This rules out a pure statistical learning explanation: if performance differences reflected only the information content of the data, experience should not matter conditional on the dataset. The result points instead to a distinct form of learning-by-doing that complements a statistical learning mechanism. Given this, it is natural to ask how investors learn to predict. In this setting, a crucial margin of adjustment is the selection and combination of the predictive variables available on the trading platform; I hypothesize that inexperienced investors design trading strategies that sub-optimally use the available predictive variables.

[2]Participants in the trading contests have access to machine learning libraries and optimization routines, and are thus fully able to exploit the high-dimensional set of predictive signals. Therefore, any behavioral frictions demonstrated by this group of subjects are informative about how machine learning tools are used by financial decision-makers more broadly (e.g., Sheng, Sun, Yang, and Zhang, forthcoming; Chen, Sialm, and Xu, 2025).

To test this hypothesis, I measure the out-of-sample informativeness of released macro signals using Random Forest models (Gu, Kelly, and Xiu, 2020) and compare informativeness to trading responses. While all strategies respond somewhat to informative signals in this setting, those of experienced traders respond significantly more strongly. This differential sensitivity to genuine predictive power is consistent with learning-by-doing: experienced investors are better able to select and combine genuinely predictive signals. Consistent with this, experienced investors with access to the macroeconomic signals achieve higher out-of-sample Sharpe ratios compared to investors in earlier trading contests without access to these signals. The benefits of return-predictive signals thus concentrate among experienced investors, in particular.

I use Heckman's (1976) two-stage framework to test whether selection effects could be driving the experience gradient. The analysis confirms that the benefits of predictive signals concentrate among experienced participants even after correcting for investor attrition. If anything, selection effects in the trading contest setting appear to bias the measured experience gradient *downward* – as indicated by a negative coefficient on the Inverse Mills Ratio – suggesting that experience effects may be even larger than uncorrected estimates imply.

Given that inexperienced investors under-react to genuinely predictive signals, then what signals *do* they adopt? I hypothesize that familiar and recognizable signals are more likely to be adopted if investors apply the availability heuristic (Tversky and Kahneman, 1973, 1974) as they construct their signal-based trading strategies. To test for this behavioral bias, I measure the familiarity of each indicator using past mentions in news and books; these measures serve as correlated proxies for how recognizable a signal is to a layperson. I find that trading intensity is higher on days when released signals are more familiar, revealing a preference for familiar and recognizable macroeconomic indicators. These results suggest that familiarity serves as a default criterion for signal selection, while only experienced investors demonstrate a willingness to adopt informative signals. Behavioral heuristics and biases thus act as another wedge between idealized statistical learning and observed human behavior in a prediction setting.

As investors learn to predict, their behavior alters along a number of additional dimensions. Examining the cross-section of pairwise correlations in trading volume, I find that experienced investors act more similarly to one another that inexperienced investors do, revealing a convergence in the predictive models (i.e., trading strategies) that they implement. Model disagreement (Cookson and Niessner, 2020; Montiel Olea, Ortoleva, Pai, and Prat, 2022) is thus partly driven by model mis-specification, and lessens among experienced investors.

Relatedly, I find that experienced investors tend to specify more complex predictive models, drawing on a greater number of signals in doing so. To arrive at this conclusion, I first extend

Martin and Nagel's (2022) model of investor behavior in a prediction setting, allowing for the possibility that an investor harbors a bias against incorporating a valid predictive variable.[3] I show that, with appropriate assumptions, this framework admits a closed-form solution to the weights investors assign to valid signals, and these weights are equivalent to those estimated by the well-known lasso machine learning technique (Tibshirani, 1996). I exploit this behavioral microfoundation of the lasso to estimate signal usage by repeatedly fitting the lasso to individual strategy returns. This analysis reveals that experienced investors incorporate more signals into their models, and are thus less averse to complexity, than inexperienced investors. My results are consistent with complexity aversion – which has been demonstrated in other, non-prediction-based settings (Sonsino, Benzion, and Mador, 2002; Oprea, 2020; Puri, 2025) – being alleviated by accumulated experience.

Having identified behavioral frictions among trading contest participants, I next examine the common stock portfolios held by actively-managed mutual funds (and thus selected by their managers). A number of studies document that such institutional investors do not appear to adopt return-predictive signals into their trading strategies (Lewellen, 2011; Edelen, Ince, and Kadlec, 2016; McLean, Pontiff, and Reilly, 2025), raising the possibility that behavioral frictions extend to mutual fund managers as well. Empirically, I measure signal adoption using quarterly portfolio holdings, building on a literature that infers characteristic tilts and portfolio preferences from disclosed positions.[4] 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). This yields a holdings-based proxy for the extent to which *each* public signal is adopted by a fund manager, and allows a unified comparison across a large cross-section of predictive signals *within* a given portfolio.

Two immediate facts emerge from analyzing mutual fund portfolio–signal tilts. First, fund managers tilt more toward signals that have been public for longer: within a portfolio and quarter, signal tilts increase with time since signal publication. This delayed adoption is consistent with a preference for familiar predictors documented above (although institutional frictions might also play a role). Second, tilts are misaligned with predictability: I find a negative relationship between portfolio–signal tilts and signals' informativeness, indicating that managers

[3] A bias against unfamiliar signals is one such example. Inspired by Cao, Han, Hirshleifer, and Zhang's (2011) interpretation of unfamiliarity as a fear of worst-case outcomes, I model an investor's bias by injecting such a fear of worst-case outcomes into her prediction problem.

[4] See, among others, Grinblatt, Titman, and Wermers (1995), Del Guercio (1996), Falkenstein (1996), Chan, Chen, and Lakonishok (2002), Bennett, Sias, and Starks (2003), Lewellen (2011), and Lettau, Ludvigson, and Manoel (2018). Holdings are an appropriate object of study because investors must actually hold the stocks implied by predictive signals to earn the associated next-period anomaly returns.

are *less likely* to adopt the most informative signals. Both patterns survive controls for fund characteristics and portfolio × quarter fixed effects that compare, within a given portfolio and quarter, which signals receive relatively greater weight. These results hold for both *ex post* (out-of-sample) and *ex ante* measures of signal informativeness.

Experience partly mitigates the misalignment between informativeness and adoption: individual managers with more accumulated experience exhibit a weaker aversion to adopting genuine predictors; i.e., the negative association between portfolio tilt and signal informativeness is less pronounced among experienced managers. This experience effect is apparent both with manager fixed effects and manager × portfolio fixed effects that absorb manager–fund matching. Thus, while the under-adoption of genuine public predictors is pervasive, experience attenuates this behavioral friction. Together with my earlier evidence from the trading contest setting, this finding suggests that the experience gradient in signal adoption is a robust feature of investor behavior.

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).[5] I present novel empirical evidence on investors' adoption of predictive signals, including in a 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 the importance of learning-by-doing (Arrow, 1962) as an important driver of predictive signal adoption, and show this form of learning drives a wedge between investor actions and pure statistical learning from data. I also document a bias toward familiar signals, extending the reach of familiarity effects beyond stock selection (Huberman, 2001; Seasholes and Zhu, 2010). Furthermore, I contribute a behavioral microfoundation to the lasso and use it to empirically document an aversion to specifying rich, complex predictive models and a preference for simplicity, which also varies with experience. These results also shed light on the drivers of model disagreement (Cookson and Niessner, 2020; Montiel Olea, Ortoleva, Pai, and Prat, 2022).

[5] In non-prediction-related settings, well-known inefficiences 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 (Gabaix, 2014; Matějka and McKay, 2015), and more general processing costs (Blankespoor, deHaan, and Marinovic, 2020).

In asset pricing, this paper helps explain why return predictability can persist after signals become public. It relates to 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 predictors (Chen and Zimmermann, 2022), I document a number of novel behavioral frictions – the necessity to learn by doing, but also familiarity bias and an experience-dependent aversion to complex predictive models – 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 complements studies of other economic agents' responses to predictive signal availability by Chen, Hwang, and Peng (2025) and Andries, Bianchi, Huynh, and Pouget (2025).

Finally, this paper relates to multiple strands of the literature on mutual funds; firstly, 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 into complex models 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.

2 Trading Contests: Institutional Setting and Data

I now describe the controlled trading contests setting, my dataset of observable outcomes, and the institutional features I am able to exploit to shed light on behavioral frictions in signal adoption.

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.[6] 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.[7] 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 A 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 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 Mln, $0.75 Mln & $0.5 Mln to the 3 best-performing investors in each contest, respectively. These conditions make the trading contests setting a realistic one.

The trading contests setting constrains participants in ways that ensure empirical compar-

[6] 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.

[7] 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 H.2, I check that results are robust to using the official score instead of the out-of-sample SR.

isons 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 that, humans play no role in the actions of their machines; for example, they do not review or approve machine trades, nor can they make their own discretionary trades. 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.[8]

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 measure the gains to investors from having access to the additional predictive variables. Sections 2.2.3 and 2.3 provide further details, and additionally describe the (irregular) release schedules of different macroeconomic indicators.

[8] 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.

2.2 Data from Trading Contests

2.2.1 Contest Leaderboard Panel

My leaderboard sample consists of 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.

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 the whole panel. Internet Appendix B 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 indexes to measure a strategy i's trading volume on calendar day τ as

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

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 E 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 which date each macroeconomic variable release 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, they are done 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 signal.

2.4 Model and Performance Heterogeneity

Differences in Performance. Table 1 summarizes investors' in-sample and out-of-sample performance during all twelve trading contests. 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.

[Insert Table 1 here]

However, their performance degenerates out-of-sample – i.e. during contest Live periods – when trading strategies can no longer be modified by investors. During 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 inter-quartile 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.

[Insert Figure 4 here]

Figure 4 shows that trading activity is also heterogeneous. I compute the pairwise correlation between the daily aggregate turnover series of every contestant's best live entry in every contest and the equivalent turnover series for every other contestant's best live entry 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.

Differences of Opinion. 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, their disagreement is likely to stem from different interpretations of exactly the same data. Cookson and Niessner (2020) term this phenomenon "model disagreement," to distinguish it from disagreement that is due to heterogeneous information.

3 Learning to Predict

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) best Sharpe Ratios and the out-of-sample (live period) best 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

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

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 with experience.[9] OLS and panel regressions both detect this learning dynamic; furthermore, the observed magnitude of this effect strengthens once fixed effects are included in columns (2) & (4). The dependent variable in columns (1)-(2) is the in-sample (backtest period) performance outcome, so the positive estimates for β in those columns suggest that investors make use of the historical data that is available to them – they are more able to increase their observed performance outcomes before entering the Live period of each contest. The dependent variable in columns (3)-(4) is the out-of-sample (Live period) performance outcome, so the positive estimates for β in those columns are consistent with previous studies that find a learning with experience effect for the (different) setting of retail investors who trade stocks (e.g. Nicolosi, Peng, and Zhu, 2009; Seru, Shumway, and Stoffman, 2010).

[9]Note that this channel of learning with experience is distinct from a statistical effect of using additional samples to form more accurate forecasts: while the number of contests a single investor participates in does increase with calendar time (i.e. length of historical samples), investors with equal levels of experience may have participated in different contests with different lengths of historical datasets available at the time the contests occurred. Time/contest fixed effects control for this statistical effect.

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:

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

Since a linear regression produces a conditional mean, this simple procedure allows me to relate average changes to the pairwise correlations between entries (LHS) to the (equalized) changes in the experience levels of the contestants who implemented the trading strategies (RHS). 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 thus resolves model disagreement, albeit gradually. This is consistent with experienced investors converging on a more similar model of the world.

4 Signal Usage in Trading Contests

I now measure how investors react to identical predictive signals. My analysis takes advantage of institutional variation in the information content of macro release days.

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 therefdore 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 without overfitting. 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, it is important to note that this comparison is a fair one, by design. 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.[10] 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,[11] 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 of maximizing her OOS Sharpe Ratio.

My procedure for constructing a benchmark predictive model that uses all the macroeconomic signal 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).[12] Note,

[10] 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.

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

[12] It is possible that these results serve as a lower bound to the extent of macroeconomic signal-based pre-

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 (Shapeley Additive Explanation) (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 these will be matched according 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:

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

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

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

Equation (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 these signals are meaningful predictors of investors'

dictability, 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.

trading activity in the first place. 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.

4.2 Adoption of Informative Predictive Signals

I now analyze the responses of contestant's 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 investors' best live trading strategies, then standardize these volume values within 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 coefficient for the β_2 coefficient 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 significantly different to zero at the 90% level. 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 more strongly the more informative a macro release day is. That is, the trading volumes of the trading strategies designed by experienced investors are much more sensitive to the information content of macro release days than of those designed by novices. The near-insignificance of the $\widehat{\beta}_2$ estimate for inexperienced investors even calls into question whether inexperienced investors respond at all to informative macro variable releases; there is no such ambiguity for the subset of experienced investors.

I conclude that experienced investors make better use of informative predictive variables than inexperienced investors do when specifying their models of the world. This occurs despite both groups of human designers sharing an identical opportunity to detect such informative predictive variables (thanks to the controlled Quantiacs setting).

4.3 Adoption of Familiar Signals

If inexperienced investors do not use genuinely predictive macroeconomic indicators – or respond only weakly to their release – then what variables *do* they favor?

Among the prior studies on (in)experience and behavioral biases, Abreu, Mendes, and Santos (2011) find that inexperienced investors are prone to one form of familiarity bias: a home

bias in their portfolio choices. It is possible that a familiarity bias such as this can influence how investors specify their models of the world. I therefore hypothesize that inexperienced investors use variables with which they are familiar – rather than determining which variables are more informative. If this familiarity bias holds investors back from maximizing their performance outcomes, and lessens with experience, this mechanism may explain why investor experience drives improved performance outcomes. I now test this hypothesis.

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 the Factiva database, and (ii) published books indexed in the Google Books database. 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:

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

Equation (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 B. Despite the distinct sources, the two familiarity indices that I construct using Equation (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, similar to 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 Equation (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 between familiarity and experience, are significantly different to zero. Therefore, all trading strategies respond more strongly to an increase in the familiarity of the macroeconomic signals being released. This result is consistent with my hypothesis that investors first reach for more familiar variables when specifying their models of the world.

Table IA.3 in Internet Appendix C 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, and results are similar across both familiarity measures.

5 Gains from Predictive Signal Availability

Inexperienced investors respond only weakly to informative macro predictive variables, and tend to rely on familiar macro predictive variables. On net, do they benefit from macro predictive variables at all? I answer this question by comparing investors who have access to macro predictive variables to investors who do not. I find that inexperienced investors do *not* benefit, on net, from having access to macro predictors.

5.1 Performance Gains Due to Macro Signals

To cleanly measure the benefits that investors derive from data, I define two groups. The Control group consists of investors during contests 1-7, when macro signals were not available on the Quantiacs platform. The Treatment group consists of investors who only traded from contest 8 onward; that is, in the environment when the additional signals were available. To be able to include fine-grained experience level indicators, I focus on investors who have experienced 1-4 contests.

The Quantiacs institutional setting implicitly controls for a variety of potential confounders by enforcing identical goals, horizons, and other common conditions upon the investors in my sample. In addition, Table IA.1 in the Internet Appendix verifies that contestants are balanced across the Treatment and Control groups with respect to their observable characteristics: Panel A displays the means of a contestant's experience level, and a contestant's relative ranking in the previous contest she took part in (for contestants who participate in multiple contests). The differences are not statistically different to zero (even at a low significance level of, say, 90%). Similarly, Panel B compares contest-level participation attributes; namely, the average level of experience of contestants per contest, the fraction of first-time participants, and the fraction of last-time participants. The relevant differences are also not statistically different to zero (including at low significance levels such as 90%). The combination of implicit controls by the institutional setting and groups that are well-balanced across observables allows me to attribute changes to investors' performance outcomes to the availability of the macroeconomic predictive variables.

[Insert Table 6 here]

The regressions in Table 6 analyze the relationship between investor experience and the

availability of additional predictive signals and the out-of-sample performance outcomes using various specifications. The dummy variable named "Macro Signals Available$_t$" indicates whether investors compete after the introduction of the additional macroeconomic indicators to the common parts of investors' information sets; i.e. whether investors belong to the Treatment group. All regression specifications in Table 6 take performance outcomes to be the excess of the out-of-sample SR over the SR from holding the benchmark index (equally-weighted buy-and-hold positions in contestants' tradeable universe of futures contracts) in order to permit valid comparisons across time periods.[13]

The regression results in Panel A of Table 6 are variants of the following linear specification:

$$\begin{aligned}&\text{Excess Live SR}_{i,t}^{Best}\\ &\quad= \beta_1 + \beta_2 \times \text{Contests Experienced}_{i,t} + \beta_3 \times \text{Macro Signals Available}_t\\ &\qquad + \beta_4 \times \text{Contests Experienced}_{i,t} \times \text{Macro Signals Available}_t + \epsilon_{i,t}. \end{aligned} \tag{11}$$

The estimate $\widehat{\beta}_4 = 0.908$ of the incremental effect of data availability on performance is positive and significant. This indicates that experience and deriving a benefit from Bigger Data are complements. The availability of the additional macro predictive variables is associated with a steepening in investors' performance dynamics, over and above the positive slope captured by the estimate $\widehat{\beta}_2 = 0.589$ for the baseline; in this case, the baseline represents the performance dynamics of investors without access to the new data.

To allay any concerns about assuming a linear relationship between experience and performance, I also relax the functional form by incorporating a dummy for every experience level, and find the effect continues to hold. The regression results in Panel B of Table 6 are variants of the following specification:

$$\begin{aligned}&\text{Excess Live SR}_{i,t}^{Best}\\ &\quad= \beta_1 + \sum_{k=2}^{4}\left[\beta_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\}\right] + \gamma_1 \times \text{Macro Signals Available}_t\\ &\qquad + \sum_{k=2}^{4}\left[\gamma_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\} \times \text{Macro Signals Available}_t\right] + \epsilon_{i,t}. \end{aligned} \tag{12}$$

In Panel B column (3), the treatment indicator is interacted with indicators for investor experience to capture the incremental effects γ_k of the availability of the new predictive variables

[13] Note that since contestants are divided into two groups, I cannot identify individual-level fixed effects. Similarly, since the dummy for the availability of new predictors is time-invariant on a per-contest level, I can no longer identify contest-level fixed effects either; I therefore control for market conditions using the benchmark portfolio's performance.

on the performance outcomes of investors with comparable levels of experience k between groups. In column (3), the interaction between the indicator for treatment and indicator variables for investor experience have positive (and significantly non-zero) coefficients $\widehat{\gamma}_3$ and $\widehat{\gamma}_4$ for higher levels of experience, in particular. For lower levels of experience, however, $\widehat{\gamma}_1$ and $\widehat{\gamma}_2$ are not statistically significantly different to zero, confirming that inexperienced investors fail to derive a net benefit from gaining access to the set of macro predictive variables.

To sum up, across both functional forms I find evidence that more experienced investors are successful in making use of the additional macroeconomic signals to better attain their objective. By contrast, inexperienced investors do not derive any incremental benefit from having access to these newly-added macro variables.

5.2 Potential Alternative Non-Learning-Based Explanations

I attribute the observed experience–performance gradient to a learning-by-doing mechanism (Arrow, 1962). In this section, I entertain (and rule out) potential alternative explanations.

5.2.1 Participation Bias

Having found that experienced individual investors derive a benefit from the availability of the macro predictive variables, I now examine the robustness of this finding to a possible selection bias between investors' experience levels and their performance outcomes. Unlike Seru, Shumway, and Stoffman (2010) and Linnainmaa (2011), modeling participation and selection is not a primary object of my study; however, attrition exists in my panel of investors, and it is therefore important to understand what direction any bias might introduce to OLS regression specifications. I therefore re-estimate the magnitude of experience effects using a Heckman (1976) two-stage model, with standard errors computed according to Greene (1981).

[Insert Table 7 here]

The first stage of the procedure consists of a probit model for the participation of the contestants in the next contest, based upon a number of covariates that I specify. I argue that two of the covariates that I make use of in the first-stage selection equation satisfy an exclusion restriction: the mean of the Google Search Index for "Quantopian"[14] and the *relative* num-

[14]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. It seems implausible to argue that search interest in and attention to a rival platform (Quantopian) could affect performance outcomes in my focal setting (Quantiacs) through any channel other than an effect on participation. Note that the rival Quantopian platform is now defunct (as announced on 29 October 2020) but was active throughout my sample period.

ber 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 7, 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.

The second-stage coefficients represent the outcome equation of interest, and these are shown in the middle section of Table 7. 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 are not in fact driven by selection/attrition bias or, as Seru, Shumway, and Stoffman (2010) framed it, an investor learning about her type.

More importantly, when conditioning on the availability of the new predictive variables in column (3), the estimate of the ρ parameter in the second stage of the Heckman (1976) model is negative, and therefore so is the corresponding coefficient on the Inverse Mills Ratio, which is also statistically significant. This indicates the presence of *negative selection* in an OLS estimate of the magnitude of the effect of learning with experience. To put it differently, uncorrected OLS estimates of the magnitude of the experience effect would be biased *downwards* for the investors with access to the additional predictive variables. The direction of this effect is in agreement with the intuition of Linnainmaa (2011). Furthermore, since the negative selection is concentrated among the investors who had access to the additional predictive variables, this suggests that the incremental steepening in performance dynamics due to additional data availability is likely to be even steeper than that detected by the earlier OLS regressions (Table 6 Panel A).

5.2.2 Competition Effects

In the current trading contest setting, one might wonder if the degree of competitive intensity might alter contestants' behavior and thus partly explain contestants' willingness to exploit available signals.[15] The analyses in Internet Appendix H.1 suggest that competition effects do not explain my findings.

[15] One advantage of the Quantiacs institutional setting is that investors have no price impact, which eliminates other channels for them to engage in strategic behavior.

6 Predictive Model Complexity

The analyses so far suggest investors' willingness to specify complex predictive models varies with experience. This section directly tests for such an effect. I begin by introducing a model of investor behavior that ultimately allows me to measure investors' usage of individual predictive signals. The framework that I introduce allows investors to express a bias against predictive variables, and shows that this bias can lead investors to completely ignore a subset of signals that are available to them. I also estimate this behavioral model: the results reveal an aversion to specifying complex predictive models, which lessens with experience.

6.1 Investor Behavior When Solving a Prediction Problem

6.1.1 Portfolio Choice with Historical Data

Since investors are incentivized by the contest setup to maximize their single-period out-of-sample Sharpe Ratios, the investor's objective for a particular contest is defined as

$$\max_{w} \frac{\boldsymbol{\mu}^T \boldsymbol{w}}{\sqrt{\boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w}}}, \tag{13}$$

that is, to maximize the Sharpe Ratio of a portfolio of weights $\boldsymbol{w}$ on all tradable futures contracts given a vector $\boldsymbol{\mu}$ of expected returns of those futures contracts and a variance-covariance matrix $\boldsymbol{\Sigma}$. There are no shorting constraints, and I omit any discussion of transaction costs.

In my institutional setting, investors all aim to maximize the Sharpe Ratio of their portfolios during the Live period that the trading contest is active, so their common objective can be analyzed by appealing to the single-period mean-variance framework of Markowitz (1952).[16] To solve this portfolio choice problem and attain her objective, the investor needs to know the first two moments of the returns of her tradable assets during that future period.

In reality, a prediction problem arises because the out-of-sample moments of asset returns are not known. To make progress, let us assume that $\boldsymbol{\Sigma}$ is known and so the investor must therefore estimate the unknown parameter vector $\boldsymbol{\mu}$ in order to achieve her objective.[17] Investors

[16] Note that, under relatively mild assumptions on feasible portfolios and constraint sets, the solution to the Sharpe Ratio maximization problem is simply the tangency portfolio solution to the classical Markowitz (1952) mean-variance portfolio choice problem (Cornuéjols, Peña, and Tütüncü, 2018, pp. 102-103), so there is a direct analytical link between the solutions of the Sharpe Ratio maximization problem and of the mean-variance portfolio choice problem.

[17] Empirically, it is well known that the first moment of asset returns is more difficult to estimate than the second moment. Theoretically, an asset's volatility can even be calculated exactly from continuously-observed returns. Merton (1980) discusses these empirical and theoretical considerations in detail.

in the Quantiacs setting behave consistently with this assumption: the results in Internet Appendix G suggest they draw their performance improvements primarily from improved mean returns, rather than decreases in their strategies' return volatilities.

Considering just one of those futures contracts, the investor must predict the (unknown) expected return μ in order to solve her portfolio choice problem (and to repeat the exercise for all other tradable futures contracts). She receives m signals $s_1, s_2, \ldots, s_m$ that can be used to produce a prediction $\hat{\mu}$. I begin by assuming that she is aware of the true functional form of the relationship and that it is some linear combination of the predictive signal values,

$$\mu = \sum_{i=1}^{m} b_i s_i = \boldsymbol{s}\,\boldsymbol{b}, \tag{14}$$

collecting the predictive signal values in a row vector $\boldsymbol{s}$ and linear coefficients in a column vector $\boldsymbol{b}$.

Despite knowing the true functional form, the parameters $\boldsymbol{b}$ themselves are unknown to the investor, so she must proceed by learning or estimating them based on the historical data of similar futures contracts. Recall that all futures contracts mature at predefined dates; for example, there are four S&P500 E-mini futures contracts traded on the CME that mature each year (at predefined dates in March, June, September and December). Therefore an investor who wishes to predict the expected return μ of a specific futures contract before it matures can make use of historical return data for similar futures contracts that have matured in the past.

More formally, to estimate these unknown parameters $\boldsymbol{b}$, the investor collects t previous realizations, each of which relates to the realized return v of some past futures contract and the corresponding prior signals available $s_1, s_2, \ldots, s_m$ at the time. Let us arrange these t sets of historical samples in t-dimensional column vectors $\boldsymbol{v}$ and $\boldsymbol{s}_1, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_m$, respectively. For convenience, define the $t \times m$ data matrix $\boldsymbol{S} := [\boldsymbol{s}_1 \;\; \boldsymbol{s}_2 \;\; \ldots \;\; \boldsymbol{s}_m]$. 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 $\mathrm{Err} : \mathbb{R} \times \mathbb{R} \to [0, +\infty)$ as some measure of error or deviance between its scalar arguments, her objective during the model estimation process will be to minimize the error between the observed historical realized returns $\boldsymbol{v}$ and her predictions based on the historical signal values $\boldsymbol{S}$:

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

Minimizing the errors in the predictions of these historical realized returns (15) directly improves the investor's ability to attain her objective: in fact, Best and Grauer (1991) showed an-

alytically that both over- or under-estimating assets' expected returns can lead to large changes in the mean or variance of the solution to the closely-related Markowitz (1952) portfolio choice problem. In my setting, then, both over- and under-estimates of the expected returns may lead to sub-optimal Sharpe Ratios. Knowing this, an investor who is learning to predict expected returns should seek out a functional form for the error/deviance function in (15) that penalizes both over- and under-estimates. Minimizing the root-mean-square error fulfills this goal. I therefore define this to be the (unbiased) investor's baseline prediction model. In what follows, $||\cdot||_1$ and $||\cdot||_2$ denote the ℓ_1/taxicab and ℓ_2/Euclidean norms of a vector, respectively.

Definition 1. *An unbiased investor determines the unknown parameters $\boldsymbol{b}$ by minimizing the historical prediction error*

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

The (well-known) solution to the above problem is for the investor to run an OLS regression on historical values to compute $\widehat{\boldsymbol{b}}$, and then predict the expected return according to Eqn. (14).

6.1.2 Incorporating Behavioral Frictions Into the Investor's Prediction Problem

In my characterization, the investor has well-defined preferences relating to Sharpe Ratio maximization, as required by the Quantiacs institutional setting. Much like the scenario analyzed by Martin and Nagel (2022), she faces a prediction problem, in predicting futures contracts' expected returns from historical data. I now show how notions of irrationality or bias can be incorporated into this scenario by adding a key deviation from the rational baseline.

I continue to maintain the baseline functional form for the futures contract's expected return (14), and the assumption that the investor has access to a dataset of historical signals and their realizations for similar futures contracts. I now assume, in addition, that the investor is biased against incorporating certain signals. For instance, the investor can express an aversion to unfamiliar variables in her predictive model; in a similar spirit to Cao, Han, Hirshleifer, and Zhang (2011), I capture this aversion to the unfamiliar as a fear of worst-case outcomes.

Definition 2. *A biased investor determines the unknown parameters $\boldsymbol{b}$ by considering the worst-case error that may result for any given choice of parameter values,*

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

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 an uncertainty set*

$$\mathcal{U} := \left\{ [\boldsymbol{u}_1 \ \boldsymbol{u}_2 \ \ldots \ \boldsymbol{u}_m] : ||\boldsymbol{u}_i||_2 \leq \delta_i \ \forall \ i = 1, \ldots, m \right\} \tag{18}$$

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

Definition 2 frames the biased investor's prediction problem as her attempting to minimize the worst-case prediction error while a malevolent opponent (Nature) conspires to maximize it up to the constraints permitted by $\mathcal{U}$. The higher the variable-specific bounds δ_i perceived by the investor, the worse the worst-case error and the more conservative she will be. An investor who is averse to some unfamiliar variable indexed by x will act as if she expects Nature to introduce disturbances up to magnitude δ_x to the historical values $\boldsymbol{s}_x$ of this variable in exactly such a way that it would maximize the investor's overall prediction error.

I will shortly describe a simplified version of this setup that delivers a closed-form solution and the intuition for why the biased investor will underweight – and may even ignore – current signal values, even though they determine the asset's expected return by definition (Eqn. 14). An investor who behaves according to Definition 2 is thus consistent with this paper's empirical findings that investors may choose to underweight even genuine predictive variables.

Incorporating worst-case scenarios into the investor's objective function (17) has a parallel with the setup of a zero-sum game, or indeed the well-established literature on ambiguity aversion. Notably, Epstein and Schneider (2008) and Illeditsch (2011) model the behavior of an investor responding to a (single) signal of unknown precision. Another related work by Garlappi, Uppal, and Wang (2007) models ambiguity aversion in portfolio choice as a constraint on the investor's perceived (squared) confidence interval of the expected return of an asset. There are also important differences between my approach and this literature. First, the investor's prediction problem in my case specifically incorporates a (crucial) role for historical data. Second, I do not rely on any probabilistic assumptions – not even the existence of a random variable. Third, as I will show shortly, investor behavior in my setup can easily be taken to the data thanks to strong connections with the machine learning literature.

I now show that, given an investor-specific penalization parameter, the biased investor's problem is analogous to that of running the well-known Lasso machine learning technique on the historical data that she possesses.

Assumption 1. *Assume that* $\delta_i = \delta \ \forall \ i = 1, \ldots, m$*.*

Proposition 1. *Under Assumption 1, a biased investor solves her original problem* (17) *by solving an equivalent formulation*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \frac{1}{2}||\boldsymbol{\nu} - \boldsymbol{S}\boldsymbol{b}||_2^2 + \lambda||\boldsymbol{b}||_1, \tag{19}$$

where $\lambda \geq 0$ *is a scaling of* δ *in* (18).

The Lasso prediction problem (19) has been studied extensively in the machine learning literature. As a model of investor behavior, it connects the magnitude of the investor's familiarity bias λ with the extent to which she underweights genuine predictive variables. I now make a further assumption that delivers closed-form predictive variable weights to make this point clearly.

Assumption 2. *Assume that the data matrix* $\boldsymbol{S}$ *is orthonormal:* $\boldsymbol{S}^T\boldsymbol{S} = \boldsymbol{I}$.

Proposition 2. *Under Assumption 2, the biased investor will solve her prediction problem* (19) *by predicting*

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

where $\boldsymbol{s}$ *is an m-dimensional row vector consisting of the m predictive signals to the currently traded asset's expected return* μ*, and* $\widehat{\boldsymbol{b}}$ *is an m-dimensional column vector of weights whose elements are defined by*

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

Figure 5 illustrates the functional form given by Equation (21). Over the region $|\boldsymbol{s}_k^T\boldsymbol{\nu}| \leq \lambda$ of the input domain, a biased investor will entirely ignore a predictive variable k by choosing the weighting parameter $\widehat{b}_k = 0$. The larger the magnitude of the investor's bias λ, the more likely that she will ignore any predictive signals. This simplified setting corresponds to an investor who applies her familiarity bias equally to all predictive variables, although all variables k will differ in their historical predictive contributions $\boldsymbol{s}_k^T\boldsymbol{\nu}$ and so will still be treated differently by the investor.

[Insert Figure 5 here]

6.1.3 Consequences of Investor Bias

Under-Reaction & Model Mis-Specification. One interpretation of the biased investor's model of the world (21) is to note that $\boldsymbol{s}_k^T\boldsymbol{\nu}$ would simply be the parameter value that the decision-maker would have specified *if* she had used OLS regression to solve her problem, under Assumption 2. Therefore, the investor specifies parameter values $\widehat{\boldsymbol{b}}$ that are "shrunken"

in comparison to what they would have been had she used OLS regression; this is an example of "soft-thresholding," as illustrated in Figure 5. Even when predictive variables are not ignored entirely, the soft-thresholding effect reduces their magnitudes in comparison to the correctly-specified model of the world (Definition 1) in which the investor would have simply run an OLS regression on her historical dataset. The investor's familiarity bias thus leads her to under-react to predictive signals.

Market Inefficiency & Realized Predictability. The familiarity bias that I investigate in this section has implications for market efficiency. In the most striking case, Proposition 2 implies that any signal s_k to the asset's expected return may not find its way into the price if the historical signals $\boldsymbol{s}_k$ contributed to predicting (historical) expected returns by an amount that falls below some threshold. Even when all variables are incorporated, market inefficiency may result — to see this, consider the case of a single representative investor with a λ parameter that captures her bias. This representative agent setup corresponds closely to Martin and Nagel (2022)'s model of a Bayesian learner who has a prior that is parameterized by an equivalent λ parameter. Martin and Nagel (2022, Proposition 6) argue that a prior that is incorrectly specified – i.e. with a value of λ that is excessively high – "should show up in the data as out-of-sample predictable returns" to an econometrician, since the representative agent under-weights predictive information. A familiarity bias in how investors make use of data can therefore impede market efficiency, and is a potential explanation for the existence of out-of-sample return predictability in the empirical asset pricing literature.

Sparsity & Overconfidence. Since a biased learner may ignore valid predictive signals (Proposition 2), she effectively adopts a simplified and sparse model of the world. This lends itself to an alternative behavioral interpretation: Montiel Olea, Ortoleva, Pai, and Prat (2022) argue that economic agents who ignore valid predictive variables exhibit a form of overconfidence in how they specify their model of the world.

6.2 Empirically Measuring the Extent of Investor Bias

I now take the predictive model (19) to the data. By optimizing for the best fit at the individual investor-contest level, I estimate which predictive variables are used by each investor in each contest. The objectives of this analysis are threefold. First, it allows me to detect whether investors underweight predictive variables severely enough that they are ignored altogether. Second, it allows me to measure individuals' usage of *all* predictive variables, beyond the subset of macroeconomic predictive variables analyzed in Section 4. And third, counting the estimated number of predictive variables employed produces a simple measure of how

strongly investors are biased; I can therefore test whether investors' familiarity bias lessens with experience, as hypothesized earlier.

6.2.1 Estimation Procedure

My estimation procedure is built upon that of Friedman, Hastie, Höfling, and Tibshirani (2007), who provide a coordinate-wise descent algorithm that numerically solves the investor's prediction problem (19) without the need for an orthonormality assumption: given a fixed bias parameter value λ, their algorithm estimates the optimal value of $\boldsymbol{b}$ in Eqn. (19).

It remains to estimate the optimal value of λ. To achieve this, I define the following procedure. First, prepare a grid of possible values for λ, lower-bounded at zero, and estimate $\widehat{\boldsymbol{b}}$ for each of these possible values $\widehat{\lambda}$. Secondly, for each pair $(\widehat{\boldsymbol{b}}, \widehat{\lambda})$, predict expected returns for each of the historical returns in the investor's dataset as $\widehat{\boldsymbol{v}} = \boldsymbol{S}\widehat{\boldsymbol{b}}$. Compare these predicted values $\widehat{\boldsymbol{v}}$ to the actually observed historical returns $\boldsymbol{v}$ by calculating the element-wise mean-squared error (MSE) between these two vectors. Finally, pick the optimal pair $(\widehat{\boldsymbol{b}}^*, \widehat{\lambda}^*)$ to be the pair $(\widehat{\boldsymbol{b}}, \widehat{\lambda})$ that minimizes this MSE.

Operationalizing this procedure requires me to supply empirical values for $\boldsymbol{v}$ and $\boldsymbol{S}$. I therefore apply my estimation procedure to the timeseries of daily portfolio returns earned by the investor in place of $\boldsymbol{v}$,[18] and define a corresponding matrix of predictive signals $\boldsymbol{S}$ that the investor had access to at the time of forming her daily portfolio. For contests in which macroeconomic predictive variables were not available, the 880 columns of $\boldsymbol{S}$ are defined to contain 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. For contests in which macroeconomic predictive variables were available, the 934 columns of $\boldsymbol{S}$ include, in addition, the latest available values (i.e. lag 1) for each of the 54 macroeconomic predictive variables. Predictive variables are standardized to a common scale. The high dimensionality of the signals matrix $\boldsymbol{S}$ illustrates the challenges investors face when making predictions in a Big Data environment (Martin and Nagel, 2022) but does not pose any practical difficulties to the procedure of Friedman, Hastie, Höfling, and Tibshirani (2007).

I perform this estimation procedure for all contest entries of all investors who take part in more than one contest. To enable valid comparisons,[19] I report the estimated number of

[18] 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.

[19] As Lemma 2 in the Appendix makes clear, estimates for λ are only comparable if the dataset used is fixed throughout, which is not the case. The estimated number of predictive variables, on the other hand, is always comparable.

predictive variables that each investor entry uses; that is, the number of non-zero elements in the corresponding vector of parameter solutions $\widehat{\boldsymbol{b}}^*$.

6.2.2 Results and Discussion

Figure 6 displays the mean number of estimated variables used by an investor according to experience level (i.e. number of contests participated in so far), split into the Treatment and Control groups that I defined in Section 5.1.

[Insert Figure 6 here]

These estimates of $\widehat{\boldsymbol{b}}^*$ indicate that investors make use of more predictive variables in the information environment in which more were available (Treatment) compared to the baseline environment (Control). However, investors of all experience levels ignore a subset of the predictive variables that are available to them. The ignored variables include both price-based and (in the Treatment group) macroeconomic predictive variables, suggesting that investor underweighting of predictive variables is a general phenomenon that extends beyond the set of macroeconomic indicators (Section 4).

Within each of the information environments, my estimates of $\widehat{\boldsymbol{b}}^*$ indicate that less experienced investors ignore more predictive variables than more experienced investors. This is consistent with the core of my hypothesized mechanism: that, as investors gain in experience, they learn to overcome their familiarity bias, and they therefore make better use of the predictive variables that are available to them. According to these results, one way in which investors make better use of predictive variables is by ignoring fewer of them: Figure 6 illustrates that each contest's worth of experience is associated with an additional 25-50 predictive variables being incorporated into investors' models of the world.

7 Evidence From Mutual Fund Portfolio–Signal Tilts

This section turns to a second, complementary setting: an examination of mutual funds' common stock portfolios and their tilts to signals that predict returns.

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 tilts. I focus on domestic equity funds, exclude incubating funds, and exclude index funds following standard practice (Ben-David, Li, Rossi, and Song, 2022). These filters yield a sample of actively managed mutual fund portfolios for which I can compute portfolio tilts.

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.

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 I provides detailed definitions of these characteristics.

The default measure for a signal's informativeness in the mutual fund analyses is in the spirit of McLean and Pontiff (2016): I use the *ex post* mean returns of long–short portfolios 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). As a robustness check, I show that results are similar when I instead use the *ex ante* returns up to t. Figure 7 summarizes the empirical distribution of these measures of signal predictive power throughout the common sample period.

[Insert Figure 7 here]

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 $s_{c,i,t}$:

$$\text{Portfolio Signal Exposure}_{p,c,t} \triangleq \sum_i w_{p,i,t}\, s_{c,i,t}. \tag{22}$$

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

$$\text{MKT Signal Exposure}_{c,t} \triangleq \sum_i w_{MKT,i,t}\, s_{c,i,t}. \tag{23}$$

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:

$$\text{Portfolio Signal Tilt}_{p,c,t} \triangleq \text{Portfolio Signal Exposure}_{p,c,t} - \eta_{p,t}\, \text{MKT Signal Exposure}_{c,t}, \tag{24}$$

where $\eta_{p,t} \triangleq \sum_i w_{p,i,t}$ is the portfolio's overall net directional exposure. For a long-only portfolio, 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, $\text{Portfolio Signal Tilt}_{p,c,t}$ 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. Figure 8 summarizes the empirical distribution of these tilts across portfolios.

[Insert Figure 8 here]

Tilts and Alpha. Before examining differential tilts to various signals within the same portfolio (Eqn. (24)), 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:

$$\overline{\text{Portfolio Tilt}}_{p,t} \triangleq \frac{1}{N_t} \sum_c \text{Portfolio Signal Tilt}_{p,c,t}. \tag{25}$$

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 8 here]

Table 8 shows that a higher aggregate tilt (Eqn. (25)) 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 confirms that portfolio–signal tilts generate outperformance compared to the market portfolio.

7.2 Tilts, Signal Informativeness, and Manager Experience

Table 9 relates portfolio–signal tilts to signal age and a direct measure of a signal's *ex post* informativeness, defined as the signal's subsequent long–short mean return (from $t+1$ onward) in Panel A; for robustness, Panel B repeats the test with an *ex ante* (backward-looking) signal informativeness measure. Across specifications, the coefficient on time elapsed since signal publication is positive and highly significant, indicating that funds load more strongly on signals that have been public for longer; this fact suggests managers could be influenced by the familiarity or recognizability of the signal.

[Insert Table 9 here]

Additionally, tilts are *negatively* related to signal predictive power: managers are less likely to adopt – or more likely to tilt against – signals that are *more* informative out-of-sample. This negative association suggests that signal adoption is not simply a rational response to predictive performance. Both forms of misalignment are robust to adding standard fund controls and, most stringently, to portfolio × quarter fixed effects (column 3), which compare signals within the same portfolio and quarter while absorbing time-varying portfolio-level determinants of holdings, such as mandates.

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 10 here]

The results shown in Table 10 confirm that experience reduces the misalignment between signal informativness and adoption. The positive and signficant coefficient on manager experience shown 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. The specification in column 2 further includes an interaction term between manager experience and signal informativeness, and reveals that experienced managers tilt less strongly away from informative signals (i.e., they exhibit a weaker negative relation between tilts and predictability). Columns 3 and 4 show that this finding is robust to the inclusion of more stringent fixed effects, including time effects.

Further Robustness Checks. In unreported results, I re-construct the predictive signals $s_{c,i,t}$ using different approaches to the baseline definition (deciles using NYSE breakpoints) and recompute portfolio tilts accordingly. I find that the results in Tables 9 and 10 are robust to using both percent ranks and simple deciles excluding microcaps as alternative signal construction methods.

8 Conclusion

Across two different, yet related settings, I find that human experience is a crucial determinant of predictive signal adoption. Moreover, investors demonstrate a preference for familiar and recognizable signals, as well as an aversion to specifying complex predictive models. I document a positive experience gradient for performance and the appropriate adoption of valid predictive signals; this implies an important role for human skill, as well as a complementarity between the human decision-maker and the data-driven signal.

These findings have implications for our understanding of market efficiency and the persistence of return predictability. The behavioral frictions I document – familiarity bias and experience-dependent complexity aversion – act as psychological limits to arbitrage that slow the incorporation of public information into prices. Even when signals are freely available and genuinely informative, investors may fail to exploit them due to behavioral barriers rather than rational constraints. This mechanism helps explain why the post-publication decline in signal informativeness documented by McLean and Pontiff (2016) is only partial: behavioral frictions could act as a limit to arbitrage even after information becomes public.

More broadly, this paper contributes to understanding how economic agents use predictive

information and machine learning 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. Familiarity bias, complexity aversion, and the gradual accumulation of experience shape this incorporation process, with important consequences for market efficiency and the distribution of investment returns. As predictive technologies become increasingly sophisticated and accessible, understanding these behavioral mechanisms becomes ever more critical for explaining observed patterns in financial markets and beyond.

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Appendix

Proofs

To show Proposition 1 requires two lemmas. The first is by Xu, Caramanis, and Mannor (2010), and the second also relies on results by Tian, Loftus, and Taylor (2018).

Lemma 1 (Xu, Caramanis, and Mannor (2010) Theorem 1). *The optimization problem*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \max_{\boldsymbol{U}\in\mathcal{U}} ||\boldsymbol{v} - (\boldsymbol{S}+\boldsymbol{U})\boldsymbol{b}||_2 \tag{26}$$

with uncertainty set $\mathcal{U}$ defined by

$$\mathcal{U} := \left\{[\boldsymbol{u}_1\ \boldsymbol{u}_2\ \ldots\ \boldsymbol{u}_m] : ||\boldsymbol{u}_i||_2 \leq \delta_i\ \forall\ i = 1,\ldots,m\right\} \tag{27}$$

is equivalent to the optimization problem

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2 + \sum_{i=1}^{m} \delta_i |b_i|. \tag{28}$$

Proof. See Xu, Caramanis, and Mannor (2010) Theorem 1. □

Lemma 2. *The optimization problem*

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2 + \delta||\boldsymbol{b}||_1 \tag{29}$$

is equivalent to the optimization problem

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \frac{1}{2}||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2^2 + \lambda||\boldsymbol{b}||_1 \tag{30}$$

with the one-to-one change of parameters

$$\lambda = \frac{\delta a_1}{\sqrt{1-\delta^2 a_2}} \quad \Leftrightarrow \quad \delta = \frac{\lambda}{\sqrt{\lambda^2 a_3 + a_4}}, \tag{31}$$

in which each of λ, δ are monotonically increasing in the other, and where $a_1, a_2, a_3, a_4 > 0$ and are constant for any fixed dataset $(\boldsymbol{S}, \boldsymbol{v})$ and common parameter estimates $\boldsymbol{b}^*$.

Proof. Xu, Caramanis, and Mannor (2010, Appendix A) show that the two problems are equivalent up to a change of λ, δ parameters. Tian, Loftus, and Taylor (2018, Lemma 2) derive the

mapping between δ and λ in terms of $\boldsymbol{b}^*, \boldsymbol{S}, \boldsymbol{v}$. It is simple to show that $a_1, a_2, a_3, a_4 > 0$ in their formulation and that $\frac{\partial \lambda}{\partial \delta}, \frac{\partial \delta}{\partial \lambda} > 0$ for $\lambda, \delta > 0$. □

The proof of Proposition 1 now follows.

Proposition 1. *Under Assumption 1, a biased investor solves her original problem* (17) *by solving an equivalent formulation*

$$\min_{\boldsymbol{b} \in \mathbb{R}^m} \frac{1}{2} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2^2 + \lambda ||\boldsymbol{b}||_1, \tag{19}$$

where $\lambda \geq 0$ *is a scaling of* δ *in* (18).

Proof. Applying Lemma 1 to the optimization problem in Definition 2 with $\delta_i = \delta \ \forall i$ shows that (17) is equivalent to the following optimization problem:

$$\min_{\boldsymbol{b} \in \mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2 + \delta ||\boldsymbol{b}||_1. \tag{32}$$

By Lemma 2, (32) is equivalent to (19), with the mapping between λ, δ given by the lemma. The optimization problems (17) and (19) are thus equivalent. □

The result in Proposition 2 is due to Tibshirani (1996), who did not provide a proof. For completeness, a brief proof follows.

Proposition 2. *Under Assumption 2, the biased investor will solve her prediction problem* (19) *by predicting*

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

where $\boldsymbol{s}$ *is an m-dimensional row vector consisting of the m predictive signals to the currently traded asset's expected return* μ*, and* $\widehat{\boldsymbol{b}}$ *is an m-dimensional column vector of weights whose elements are defined by*

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

Proof. I start from the formulation (19). As the ℓ_1 norm is not differentiable, I follow Lee, Sun, Sun, and Taylor (2016) in writing the (necessary and sufficient) Karush–Kuhn–Tucker conditions for a solution in terms of the subdifferential $\partial(||\boldsymbol{b}||_1)$:

$$\boldsymbol{0} \ \in \ \boldsymbol{S}^T(\boldsymbol{S}\widehat{\boldsymbol{b}} - \boldsymbol{v}) + \lambda \partial(||\boldsymbol{b}||_1) \tag{33}$$

The orthonormality assumption $\boldsymbol{S}^T\boldsymbol{S} = \boldsymbol{I}$ then simplifies it to

$$\boldsymbol{0} \ \in \ \widehat{\boldsymbol{b}} - \boldsymbol{S}^T\boldsymbol{v} + \lambda \partial(||\boldsymbol{b}||_1). \tag{34}$$

Note that each element $\widehat{b}_k$ of $\widehat{\boldsymbol{b}}$ does not depend on other elements of $\widehat{\boldsymbol{b}}$:

$$0 \;=\; \widehat{b}_k - \boldsymbol{s}_k^T \boldsymbol{v} + \lambda \widehat{z}_k, \tag{35}$$

where $\widehat{z}_k = \text{sign}(\widehat{b}_k)$ when $\widehat{b}_k \neq 0$ and the set $[-1, +1]$ otherwise. The result (21) then follows.

□

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.

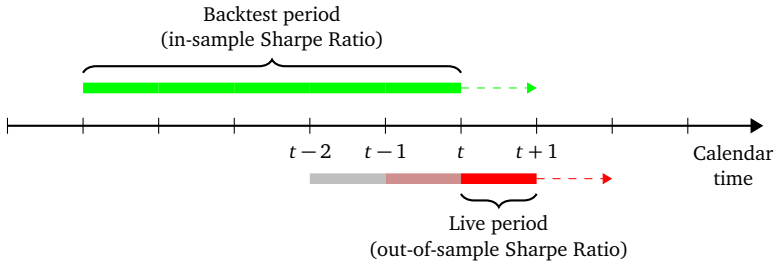


Figure 2: Distinction Between Macro Signal Release Days and Macro Signal Availability. Contestants take part in one or more trading contests t by entering trading strategies that run over an extended calendar period. The historical periods of all contests overlap in calendar time, so each historical 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).

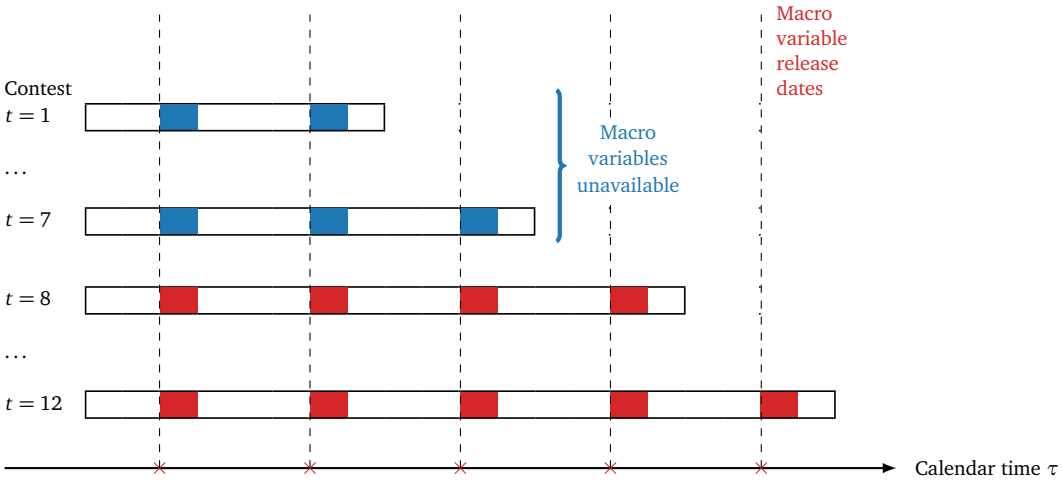


Figure 3: Variation in the Number of Signals Released on Macro Release Dates. This chart counts the number of macro variables that were released to trading strategies on the Quantiacs platform, including both in-sample/Backtest and out-of-sample/Live periods. Variables were released in monthly batches, 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."

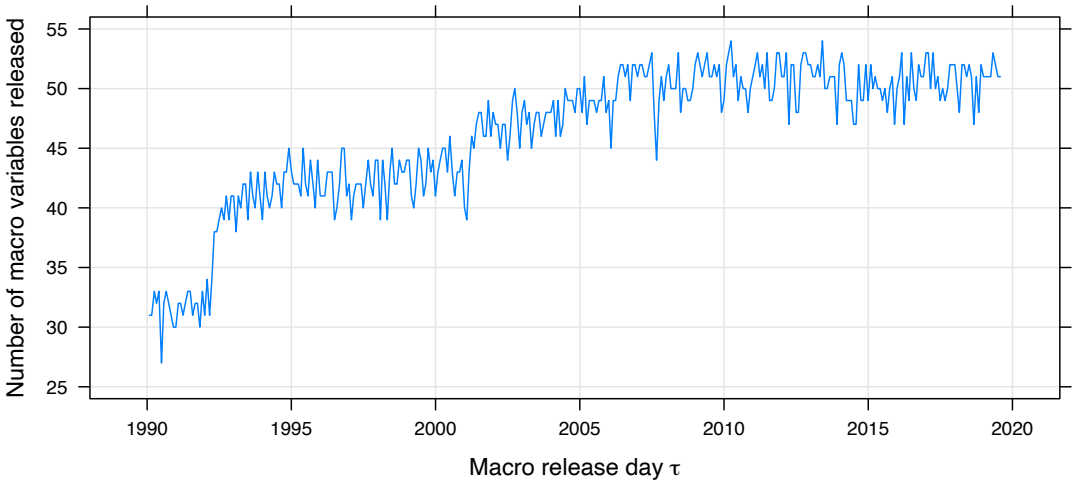


Figure 4: Cross-Sectional Mean Correlation in Trading. For each trading contest index t, this chart displays the cross-sectional mean of the pairwise correlations $\rho_{i,j,t}$ in daily turnovers for all best live entries in the contest. Self-correlations are excluded.

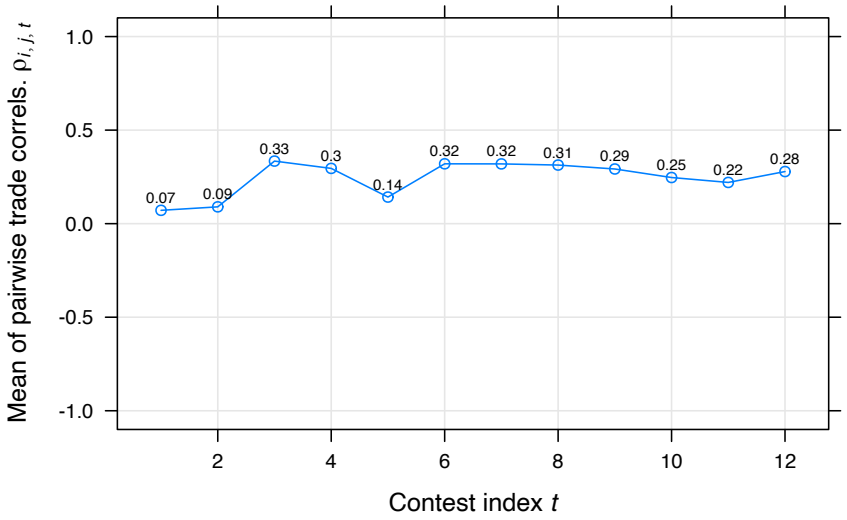


Figure 5: Soft-Thresholding. Illustration of soft-thresholding an input. The dashed line denotes the benchmark $f(x) = x$. The solid blue line $f(x) = \text{sign}(x)\max\{|x| - \lambda, 0\})$ is the result of soft-thresholding the input x at threshold λ.

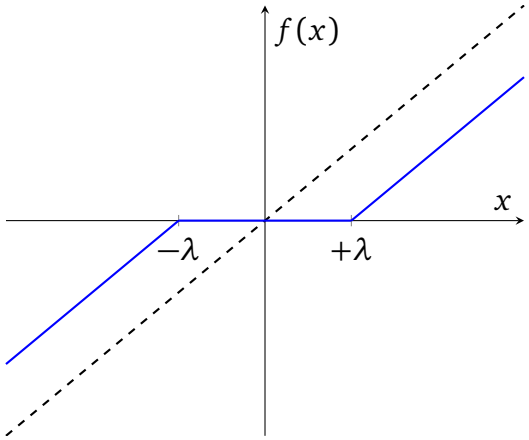


Figure 6: Trading Contest Participants' Usage of Predictive Variables. This chart shows the number of predictive variables used by investors. These are measured according to the model of investor behavior in Section 6.1.2, based on investors' daily portfolio returns and a set of predictive variables. A total of 934 variables are tested, including both return-based and macroeconomic predictive variables. The positive slopes indicate that both groups of investors make use of more predictive variables as they gain in experience. The offset indicates investors with access to more predictive variables use more of them. The split into groups of investors with and without access to macro predictive variables is the same as for the main regression specifications. Bars represent standard errors.

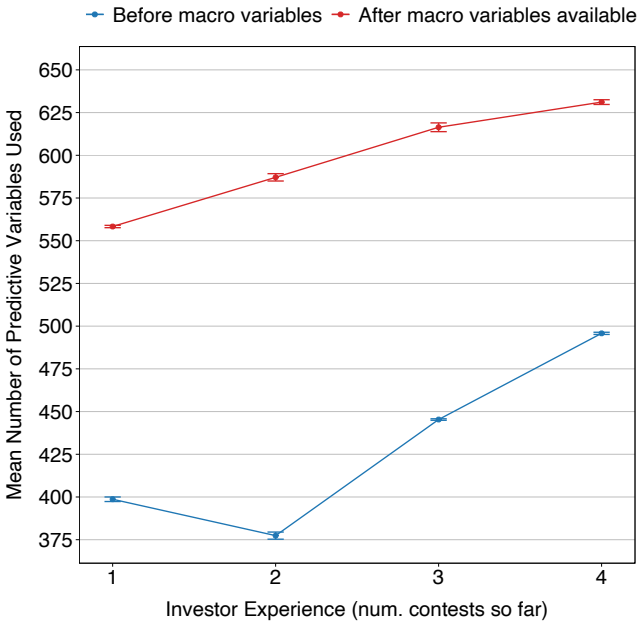


Figure 7: Stock Return Predictors' Ex-Post Mean Returns. This figure plots the distribution, across the 212 Chen and Zimmermann (2022) predictors, of each predictor's *ex post* mean return based on long–short portfolio sorts. Positive values indicate predictors whose post-publication sorts earn positive average returns. The dashed gray line indicates the sample mean.

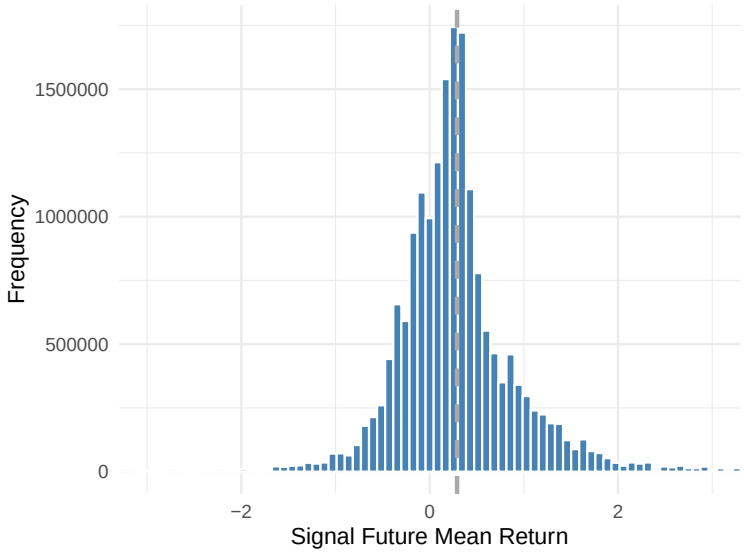
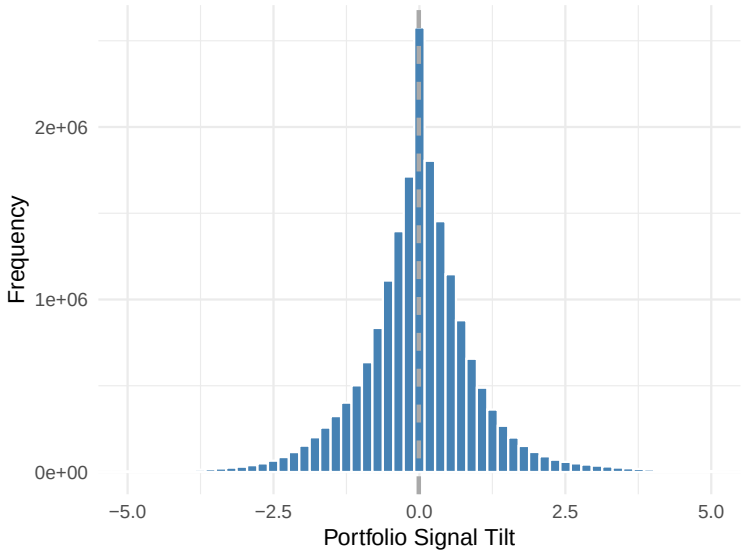


Figure 8: Portfolio–Signal Tilts. This figure plots the distribution of quarterly portfolio–signal tilts across mutual funds and predictors. Tilts are defined by Eqn. (24); positive tilts indicate active loadings toward stocks with higher predicted returns. The dashed gray line indicates the sample mean.



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 inter-quartile range, and "SD" denotes the cross-sectional standard deviation. The Entries columns summarize entries per contestant.

					Backtest/In-Sample Sharpe Ratios					Live/OOS Sharpe Ratios								
			Entries		Percentile			Dispersion		Percentile					Dispersion		Variables	
Index	Live/OOS Period	Contestants	Median	Mean	25	50	75	IQR	SD	10	25	50	75	90	IQR	SD	Price	Macro
1	2014-12-01 – 2015-01-31	13	1.00	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	2.00	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	1.00	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	1.00	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	2.50	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	1.00	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	1.00	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	1.00	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	1.00	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	1.00	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	1.00	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	1.00	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:	874	1.00	2.92														

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

	Dependent variable:			
	Backtest $SR_{i,t}^{Best}$		Live $SR_{i,t}^{Best}$	
	(1)	(2)	(3)	(4)
Contests Experienced$_{i,t}$	1.161***	1.338***	0.445**	1.261***
	(0.055)	(0.505)	(0.178)	(0.456)
Intercept	✓		✓	
Contest FEs		✓		✓
Contestant FEs		✓		✓
N	874	874	874	874
R^2	0.156	0.024	0.035	0.040

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 OLS & panel regressions for pairwise correlations of the daily turnover series of best live trading strategies 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	0.00112	0.00939	0.30492

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 a 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	0.00014	0.00034	0.00054

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	0.00014	0.00019	0.00034	0.00014	0.00029

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

Table 6: 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 best live Sharpe Ratio over the Sharpe Ratio of the benchmark index during that out-of-sample period, which effectively controls for time periods/contests. In all specifications, the dummy "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

Panel A: Linear Relationship

	Dependent variable:		
	Excess Live $SR^{Best}_{i,t}$		
	(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)
Observations	830	830	830
R^2	0.048	0.053	0.063

Panel B: Indicator Variables

	Dependent variable:		
	Excess Live $SR^{Best}_{i,t}$		
	(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)
Observations	830	830	830
R^2	0.050	0.055	0.067

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

Table 7: Ruling Out Selection Effects. 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 $SR_{i,t}^{Best}$	Live $SR_{i,t}^{Best}$	Live $SR_{i,t}^{Best}$
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	0.04	0.07	0.04
	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 8: Aggregate Mutual Fund Portfolio Tilts and Relation to *Ex Post* Fund Alpha. This table shows that aggregate portfolio tilts predict funds' next-period α. The independent variable $\overline{\text{Portfolio Tilt}}_{p,t}$ (Eqn. (25)) is the aggregated tilt of a portfolio p in the direction of return predictability at the end of year-quarter t. The dependent variables consist of monthly means (%) of the portfolio's α over the 12-month period following t. The α calculations are based on gross-of-expense-ratio portfolio returns in columns 1–2 , and on net-of-expense-ratio portfolio returns in columns 3–4. The α calculations are with respect to the CAPM in columns 1 & 3, and with respect to the Carhart (1997) 4-factor model in columns 2 & 4. The sample consists of active mutual funds for which a sole manager could be identified.

Dependent Variables:	Gross CAPM $\alpha_{p,t}$	Gross Carhart $\alpha_{p,t}$	Net CAPM $\alpha_{p,t}$	Net Carhart $\alpha_{p,t}$
	(1)	(2)	(3)	(4)
$\overline{\text{Portfolio Tilt}}_{p,t}$	0.5883**	0.3708*	0.5884**	0.3692*
	(0.2486)	(0.2109)	(0.2486)	(0.2107)
Portfolio FEs	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
N	22,223	22,223	22,292	22,292
R^2	0.31184	0.55448	0.31427	0.55787

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

Table 9: Mutual Fund Portfolio Tilts, Signal Familiarity, and Signal Informativeness. This table shows the results of regressing portfolio–signal tilts (Eqn. (24)) on the informativeness of a signal and the time elapsed since the signal was publicy disseminated in the form of an academic publication. The informativeness of the signal for characteristic c is computed from *ex post* signal returns in the period following t (Figure 7) in *Panel A*, and on *ex ante* signal returns up to time t in *Panel B*. *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)
Panel A: Signal Informativeness Measured *Ex Post*			
Signal Informativeness$_{c,\,t+1\text{ onwards}}$	-0.1402***	-0.1408***	-0.1400***
	(0.0139)	(0.0141)	(0.0138)
Log Months Since Signal Publication$_{c,t}$	0.0474***	0.0479***	0.0473***
	(0.0065)	(0.0065)	(0.0065)
R^2	0.03671	0.03716	0.04810
Panel B: Signal Informativeness Measured *Ex Ante*			
Signal Informativeness$_{c,\,\text{up to}\,t}$	-0.0407***	-0.0414***	-0.0406***
	(0.0094)	(0.0095)	(0.0094)
Log Months Since Signal Publication$_{c,t}$	0.0541***	0.0546***	0.0539***
	(0.0065)	(0.0066)	(0.0065)
R^2	0.02986	0.03024	0.04127
Controls and Fixed Effects			
Portfolio FEs	✓	✓	
Quarter FEs	✓	✓	
Fund & Portfolio Controls$_{p,t}$		✓	
Portfolio × Quarter FEs			✓
N	3,415,835	3,294,060	3,415,835

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

Table 10: Experience Effects Within Fund Manager. This table shows the results of regressing portfolio–signal tilts (Eqn. (24)) on *ex post* 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	0.03356	0.03372	0.03643	0.03741

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

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A 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.1 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.2 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.3.

Figure IA.1: 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.

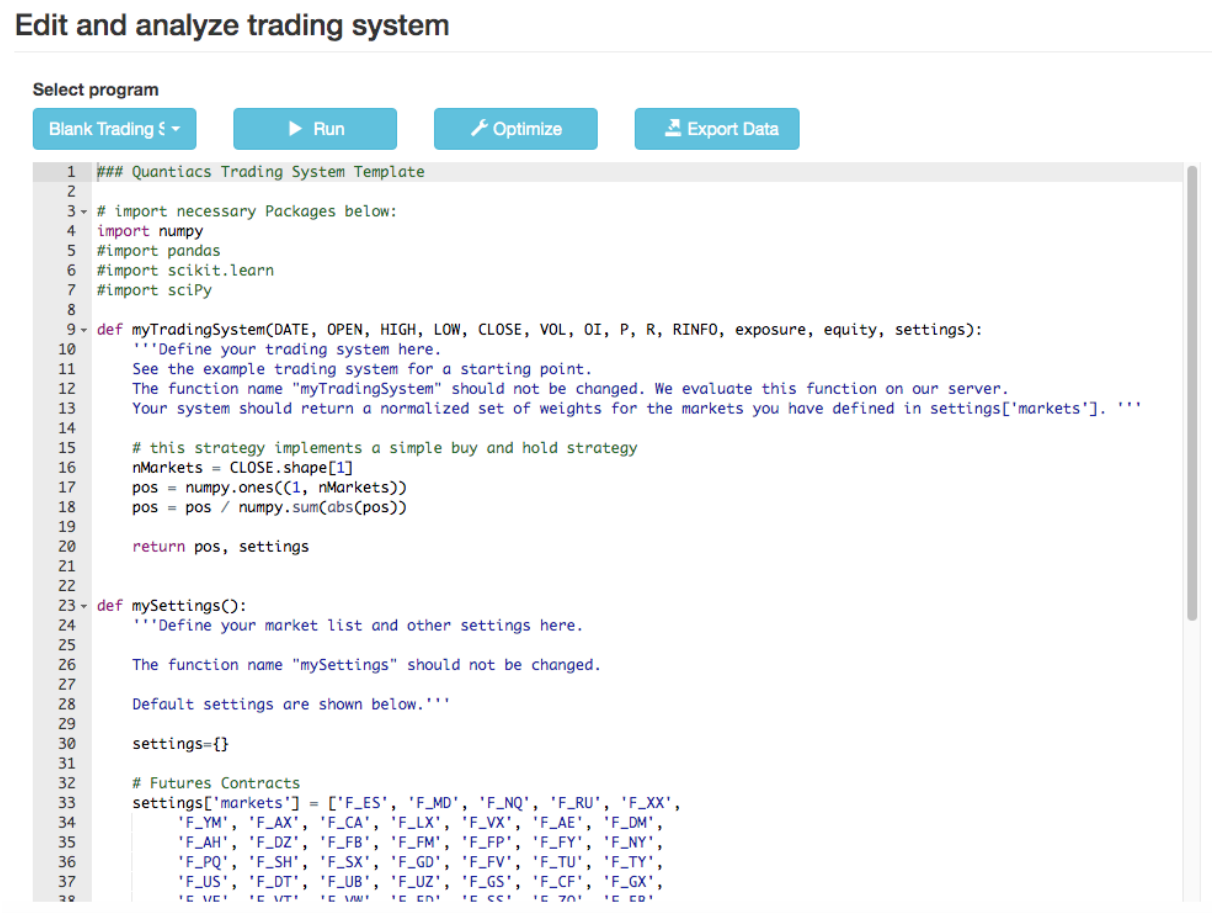


Figure IA.2: Backtesting Prior to Contest Entry. Example of in-sample backtest results for a systematic trading strategy, before an entry is submitted. At this point, a trading contest has not (yet) begun.

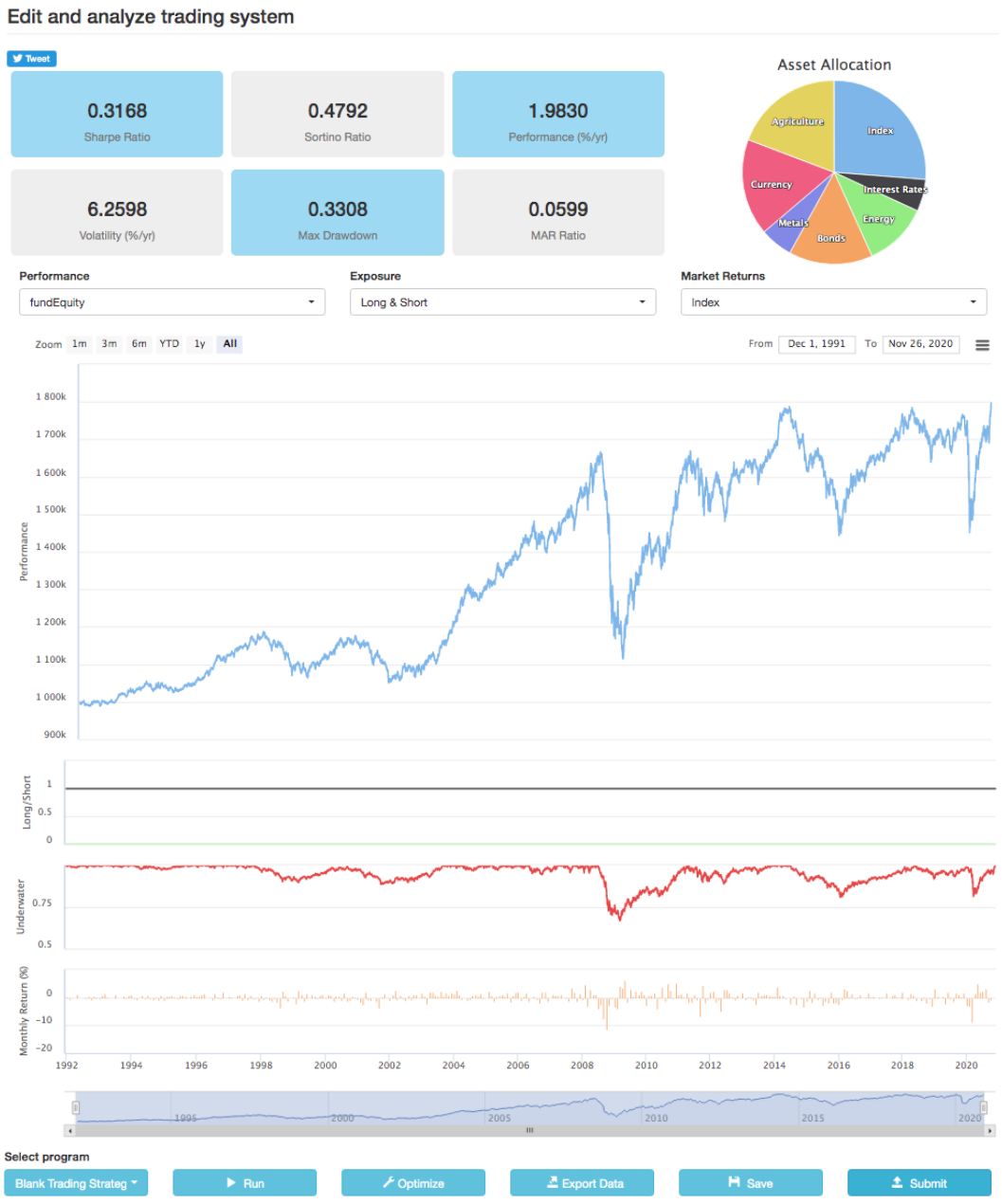
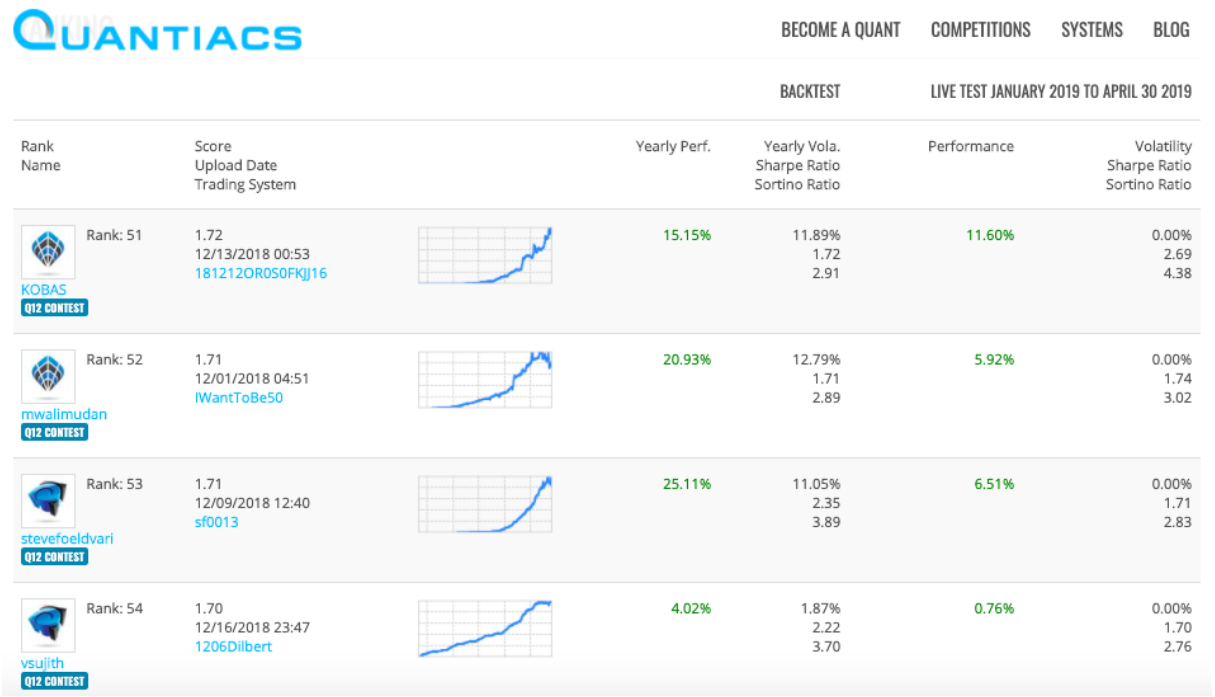


Figure IA.3: Contest Outcomes Revealed Once Live Period Ends. Excerpt from a contest leaderboard, showing both in-sample and out-of-sample Sharpe Ratios, after a trading contest has ended. The "live test" performance metrics were calculated once the contest period (1 January to 30 April 2019, in this case) had ended.



B Additional Figures for Trading Contest Analyses

Cross-Sectional Dispersion in OOS Performance Outcomes. Figure IA.4 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.5 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 predictive variables were introduced in between contests 7 & 8; i.e. the introduction of the additional predictive variables does not appear to be a structural break in terms of participation.

Informativeness vs. Familiarity at the Individual Macro Signal Level. Figure IA.6 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.7 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.4: 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.

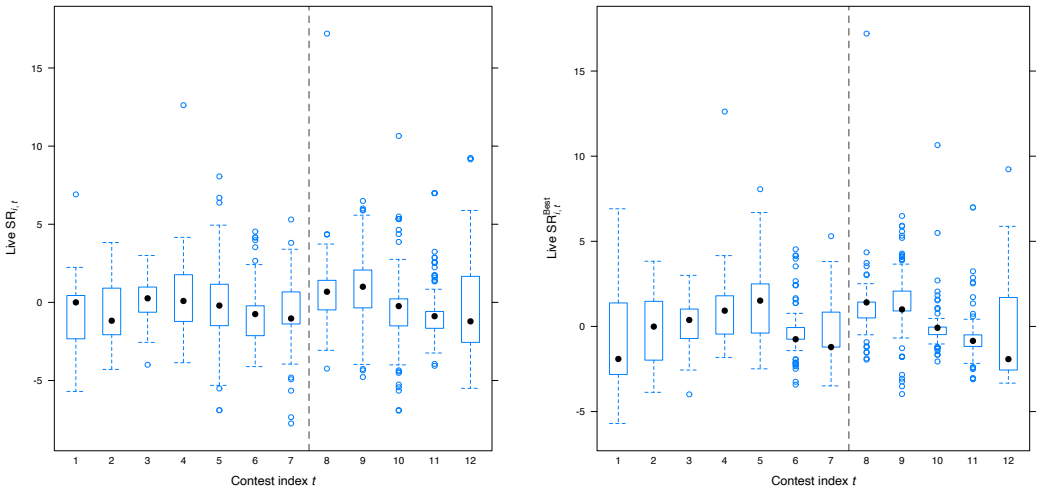


Figure IA.5: Participation and Attrition. Proportions of contestants for whom this is the first contest, and those for whom this is the last contest (with breakdowns of the latter).

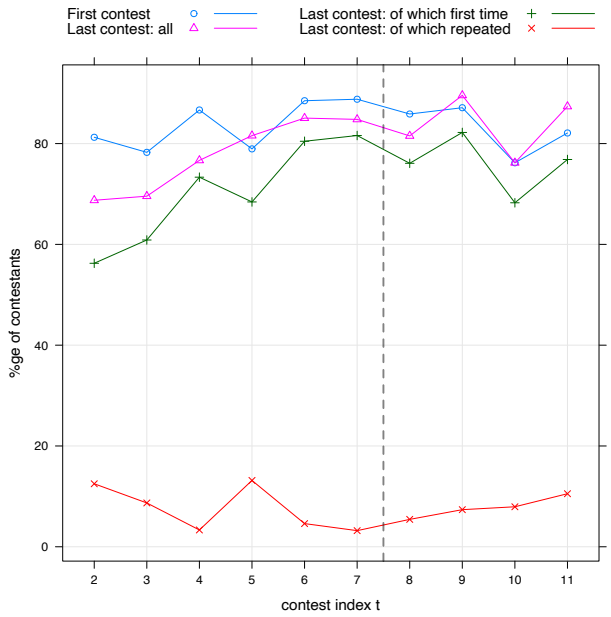


Figure IA.6: Concentration Measures of Individual Macro Signal Informativeness and Familiarity. Percentages of the total annual macro variable informativeness, and of the total annual macro variable mentions in news articles and books (i.e. familiarity), that are attributed to the top 3-ranked (LHS) and top 10-ranked (RHS) individual macro variables, for each year.

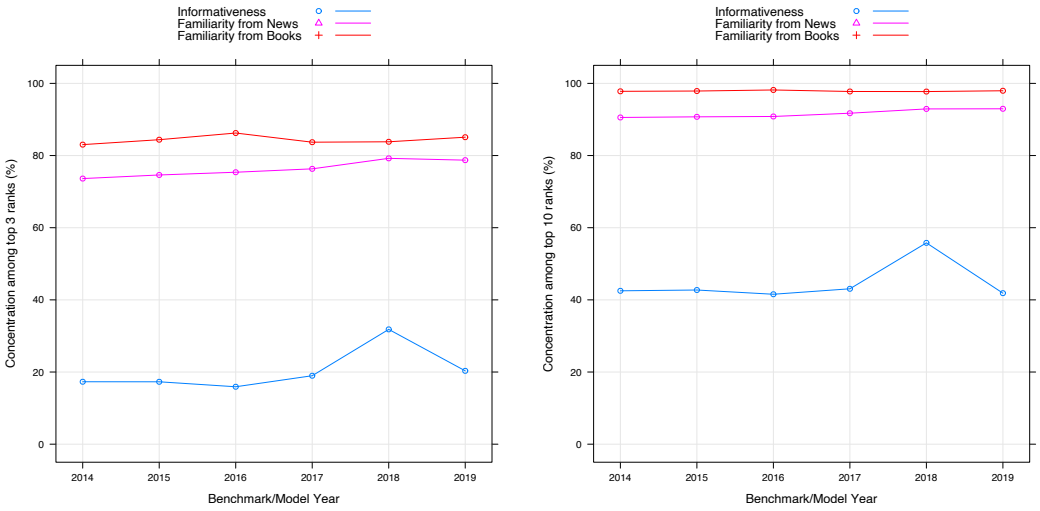
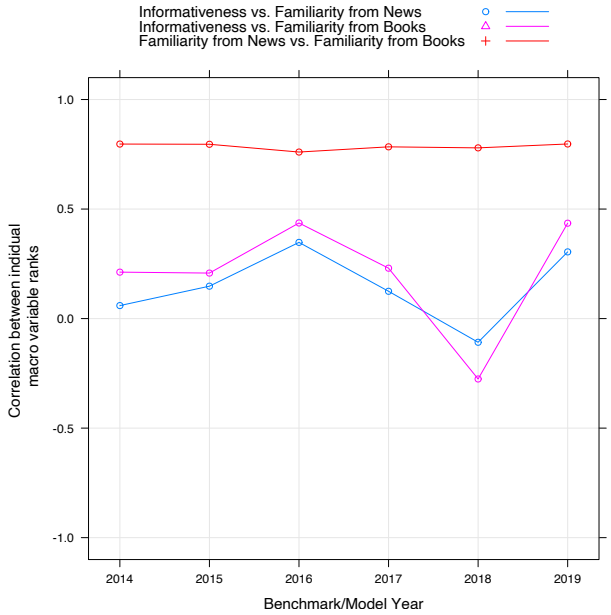


Figure IA.7: Rank-correlations of Individual Macro Signal Informativeness and Familiarity. Correlations between macro variable informativeness and familiarity rankings. For both familiarity measures, rankings are computed each year using article and book mentions for that year. The informativeness measures are computed according to a benchmark machine learning model that uses historical data up to the end of the prior year.



C Additional Tables for Trading Contest Analyses

C.1 Leaderboard Treatment vs. Control Information Environment Groups

The Treatment & Control sub-samples defined in Section 5.1 are summarized in Table IA.1, which also includes a test for non-balance across observable characteristics.

Table IA.1: Investor Balance Across Information Environments. This table describes the balance of investor populations across the Control & Treatment groups, as defined in Section 5.1: investors in the Control group have no access to macroeconomic predictive variables, and investors in the Treatment group do. *Panel A* shows participation attributes of individual contestants i at contests t. *Panel B* shows participation attributes aggregated at the contest level (t). The comparisons are of observable attributes before vs. after the additional macroeconomic indicators were made available to contestants by the trading platform.

Panel A: Individual-Level Balance

	Control (N=289)		**Treatment** (N=502)			
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff. in Means**	**p value**
Contests Experienced$_{i,t}$	1.0796	0.3183	1.1058	0.3985	0.0262	0.3108
Percentile(Score$^{Best}_{i,t-1}$)	0.6445	0.2570	0.7102	0.2588	0.0657	0.3592

Panel B: Contest-Level Balance

	Control (N=6)		**Treatment** (N=4)			
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff. in Means**	**p value**
Mean$_t$(Contests Experienced$_{i,t}$)	1.2092	0.0544	1.2191	0.0810	0.0099	0.8389
Fraction of first-time contestants at t	0.8415	0.0534	0.8580	0.0396	0.0165	0.5914
Fraction of last-time contestants at t	0.7813	0.0778	0.8542	0.0567	0.0729	0.1263

Note: the reported p-values are from two-sided t-tests. For mechanical reasons, in Panel B the first contest is excluded (because its fraction of first-time contestants would be 1.0) and the last contest is excluded (because its fraction of last-time contestants would be 1.0).

C.2 Daily Macro Signal Informativeness vs. Familiarity

Table IA.2 lists the top 20-ranked macro variables by informativeness and by each familiarity measure, aggregated over the benchmark period.

Table IA.3 combines the regression specifications of Tables 4 and 5 to jointly analyze the responses of turnover to macro release day informativeness and macro release day familiarity.

Table IA.2: 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

Table IA.3: Trading Strategy Responses to Both Macro Signal Informativeness and Familiarity. Standardized daily turnover of best live 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	0.00055	0.00060	0.00054	0.00059

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

D 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.

D.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.4.

Table IA.4: 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

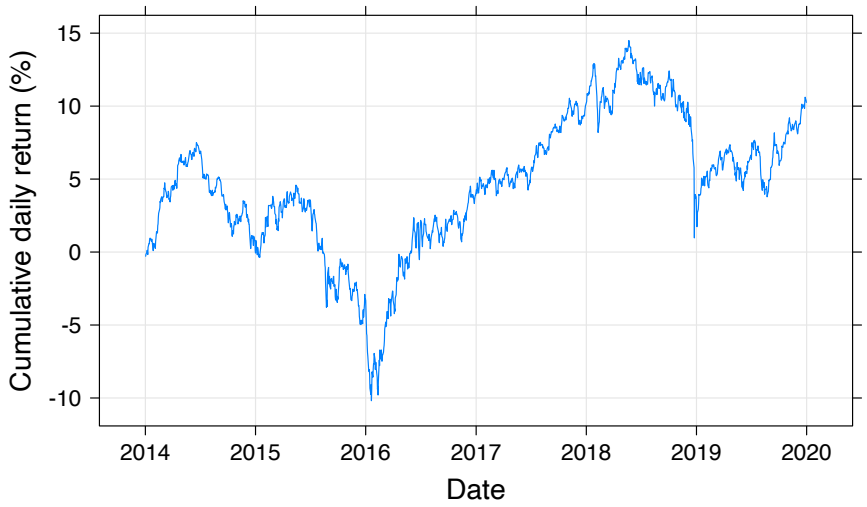
	Quantiacs ticker	Name	Type	Matching Bloomberg base code
53	F_NQ	E-mini Nasdaq 100 Index	Index	NQ Index
54	F_NR	Rough Rice	Agriculture	RR Comdty
55	F_NY	Nikkei 225	Index	NI Index
56	F_O	Oats	Agriculture	O Comdty
57	F_OJ	Orange Juice	Agriculture	JO Comdty
58	F_PA	Palladium	Metal	PA Comdty
59	F_PL	Platinum	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

D.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.1). 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.8.

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



E 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.5.

Table IA.5: 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 Confirming that Contestant Strategies Incorporate Macro Signals

F.1 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 trading strategies that did not actually have access to these macroeconomic indicators (see Figure 2 in the paper).

I regress the standardized daily trading volumes of investors' best Live-period entries 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.6. The first two columns focus on investors who could access the macroeconomic predictive variables and use their realizations to make systematic trading decisions. The coefficient on the interaction in column (2) captures the interaction between experience and the timing of macro variable releases. Its value is positive and significant, which suggests that investors with access to the macro predictive variables trade significantly more than their own daily average on the days when new releases of these macro variables were updated on the Quantiacs trading platform.

To complete the placebo test, the second two columns in Table IA.6 focus on investors who did not have access to the macro predictors. 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.

Table IA.6: Daily Trading Volume and Macro Signal Release Days. Regressions of the daily volume (standardized) of investors' best live trading strategies 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) and (2) are for the sub-sample of investors who could access the macro variables. Columns (3) and (4) are for the sub-sample of investors who could not access the macro variables via their trading strategies.

	$\text{Volume}_{i,\tau}$			
	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
R^2	0.00000	0.00001	0.000	0.000

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

F.2 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 Equation (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 macro release days τ:

$$\text{Volume}_{i,\tau} = \alpha_i + \beta_i \times \text{Informativeness}_\tau + \epsilon_{i,\tau} \tag{36}$$

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

$$\underbrace{-\rho_{i,j}}_{\substack{\text{Trading}\\ \text{dissimilarity}}} = \gamma \times \underbrace{\delta(\widehat{\beta}_i, \widehat{\beta}_j)}_{\substack{\text{Disagreement}\\ \text{about macro}\\ \text{predictive info.}}} + \phi_t + \epsilon_{i,j}, \tag{37}$$

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 Equation (36).

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.7 presents regression results for each of the variants of Eqn. (37). 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. I shortly examine the process by which they do so.

Table IA.7: 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)
$\log\left(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\right)$	0.0486***	0.0508***				
	(0.0030)	(0.0026)				
$\log\left(1 + \lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\right)$			0.2423***	0.2866***		
			(0.0225)	(0.0362)		
$\text{arcsinh}\left(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert\right)$					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	0.343	0.380	0.338	0.420	0.345	0.428
Within R^2		0.371		0.416		0.424

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

G Realized Moments of Daily Portfolio Returns During Trading Contests

This appendix examines the realized moments of investors' daily portfolio returns, and relates them to experience and data availability.

An investor who seeks to maximize her out-of-sample portfolio Sharpe Ratio, as Quantiacs contestants do, is faced with the joint problem of maximizing the out-of-sample returns of the portfolio while minimizing their variance; this is due to the construction of the Sharpe Ratio itself. Using timeseries of trading strategy daily returns, I decompose the realized Sharpe Ratios by estimating the mean and standard deviation of these contestants' out-of-sample portfolio daily returns. I then relate these to experience levels and the availability of additional predictive variables.

I modify the specification (12) in the paper by regressing the *ex post* estimated means of the out-of-sample daily returns of trading strategies against interacted indicators for the availability of additional predictive variables and investor experience levels:

$$\begin{aligned}
&\text{Mean}_{i,t}(\text{Best Live entry daily returns}) \\
&= \beta_1 + \sum_{k=2}^{4}\Big[\beta_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\}\Big] + \gamma_1 \times \text{Macro Signals Available}_t \\
&\quad + \sum_{k=2}^{4}\Big[\gamma_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\} \times \text{Macro Signals Available}_t\Big] + \epsilon_{i,t}. \qquad (38)
\end{aligned}$$

Regression results are displayed in Table IA.8, with the dependent variable in columns (1)-(3) constructed using raw returns, and the dependent variable in columns (4)-(6) adjusting for the benchmark portfolio's daily returns as an implicit control. Whether or not the benchmark adjustment is applied, the availability of additional predictive variables is associated with higher out-of-sample mean returns for more experienced investors, and the estimates for these coefficients γ_k are significantly different to zero.

A similar modification of the main specification (12) and previous specification (38) is to regress the *ex post* estimated standard deviations of the out-of-sample daily returns of trading strategies against interacted indicators for the availability of additional predictive variables and

investor experience levels:

$$\begin{aligned}
&\text{SD}_{i,t}(\text{Best Live entry daily returns}) \\
&= \beta_1 + \sum_{k=2}^{4}\Big[\beta_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\}\Big] + \gamma_1 \times \text{Macro Signals Available}_t \\
&\quad + \sum_{k=2}^{4}\Big[\gamma_k \times \mathbb{1}\{\text{Contests Experienced}_{i,t} = k\} \times \text{Macro Signals Available}_t\Big] + \epsilon_{i,t}. \qquad (39)
\end{aligned}$$

Regression results are displayed in Table IA.9. As above, columns (1)-(3) use raw returns and columns (4)-(6) adjust for the benchmark portfolio's daily returns before estimating their standard deviation, in order to implicitly control for differing contest time periods. Once again, the conclusions do not depend on whether the benchmark adjustment is applied. While the estimates for coefficients γ_k in columns (3) & (6) again agree with intuition, this time they are mostly not significantly different to zero.

These results indicate that the improvements in out-of-sample Sharpe Ratios that are associated with the availability of additional predictive variables (in Table 6, for example) can be attributed mainly to higher out-of-sample mean returns (Table IA.8). While I also detect lower out-of-sample standard deviations, these additional effects are mostly statistically insignificant (Table IA.9).

Table IA.8: Means of Daily Trading Strategy Returns. Regressions of investors' out-of-sample daily return means against additional data availability & 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) adjusts the daily returns using the benchmark portfolio. In all specifications, the indicator "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

	Dependent variable:					
	Mean of Live daily returns (%) for contestant i's best entry in contest t					
	Raw Returns			*Excess Returns Over the Benchmark*		
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	−0.143**	−0.006	0.008	−0.159**	−0.012	0.002
	(0.066)	(0.009)	(0.006)	(0.066)	(0.009)	(0.006)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	0.165**	0.137**	0.022	0.172**	0.142**	0.025
	(0.067)	(0.057)	(0.016)	(0.067)	(0.057)	(0.016)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	0.148**	0.130*	−0.016	0.161**	0.141**	−0.018
	(0.067)	(0.067)	(0.011)	(0.067)	(0.068)	(0.014)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	0.212***	0.149***	0.067***	0.208***	0.141**	0.048***
	(0.068)	(0.057)	(0.023)	(0.068)	(0.061)	(0.018)
Macro Signals Available$_t$		−0.223**	−0.246**		−0.238**	−0.262**
		(0.098)	(0.108)		(0.098)	(0.108)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\} \times$ Macro Signals Available$_t$			0.230**			0.233**
			(0.110)			(0.110)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\} \times$ Macro Signals Available$_t$			0.270**			0.295***
			(0.109)			(0.109)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\} \times$ Macro Signals Available$_t$			0.225**			0.258**
			(0.111)			(0.110)
N	713	713	713	713	713	713
R^2	0.001	0.005	0.006	0.001	0.006	0.007

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

Table IA.9: Standard Deviations of Daily Trading Strategy Returns. Regressions of investors' out-of-sample daily return standard deviations against additional data availability & 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) adjusts the daily returns using the benchmark portfolio. In all specifications, the indicator "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

	Dependent variable:					
	SD of Live daily returns (%) for contestant i's best entry in contest t					
	Raw Returns			*Excess Returns Over the Benchmark*		
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.816***	0.705***	0.686***	0.893***	0.769***	0.747***
	(0.140)	(0.060)	(0.062)	(0.139)	(0.058)	(0.060)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	−0.389***	−0.367***	−0.226**	−0.380***	−0.355***	−0.175**
	(0.146)	(0.124)	(0.089)	(0.144)	(0.124)	(0.085)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	−0.416***	−0.401***	−0.189	−0.367**	−0.351**	−0.101
	(0.155)	(0.147)	(0.129)	(0.159)	(0.153)	(0.149)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	−0.413***	−0.362***	−0.225**	−0.478***	−0.421***	−0.316***
	(0.152)	(0.124)	(0.096)	(0.144)	(0.108)	(0.080)
Macro Signals Available$_t$		0.181	0.211		0.202	0.238
		(0.210)	(0.233)		(0.209)	(0.232)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\} \times$ Macro Signals Available$_t$			−0.279			−0.358
			(0.246)			(0.243)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\} \times$ Macro Signals Available$_t$			−0.393			−0.462*
			(0.266)			(0.275)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\} \times$ Macro Signals Available$_t$			−0.386			−0.285
			(0.245)			(0.240)
N	713	713	713	713	713	713
R^2	0.001	0.002	0.002	0.001	0.002	0.002

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

H Robustness Checks

H.1 Competitive Intensity

This appendix tests whether competitive intensity is a potential unobserved confounder to my main findings. I measure competitive intensity as the (log of the) number of contestants taking part in a given contest.

Table IA.10 shows Poisson GLM regressions that find no association between an investor's observed effort and the competitive pressures she experiences, controlling for her experience level. Furthermore, there is also no interaction with the availability of macro signals. Note that the regression specifications in this appendix 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 in Table IA.10 with any significance.

Table IA.11 analyzes the potential consequences for investor performance. As one might expect, given the previous result, the inclusion of competitive intensity does not materially alter the baseline coefficient estimates.

Table IA.10: 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. In all specifications, the indicator "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

	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

Table IA.11: OOS Performance and Competitive Intensity. Regressions of investors' out-of-sample performance (over the benchmark SR) against measures of experience, availability of additional predictive variables, and competitive intensity. In all specifications, the indicator "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

	Dependent variable:					
	Excess Live $SR_{i,t}^{Best}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-1.162^{***}	-0.970^{***}	-0.899^{***}	4.777^{***}	5.073^{***}	5.214^{***}
	(0.075)	(0.127)	(0.130)	(0.667)	(0.791)	(0.795)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$	1.332^{***}	1.293^{***}	1.044^{**}	1.033^{***}	1.054^{***}	0.684
	(0.355)	(0.359)	(0.444)	(0.347)	(0.342)	(0.426)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$	1.673^{***}	1.654^{***}	-0.004	1.428^{**}	1.390^{**}	-0.168
	(0.523)	(0.545)	(0.395)	(0.607)	(0.590)	(0.496)
$\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$	3.021^{***}	2.918^{***}	2.245^{***}	3.009^{***}	3.176^{***}	2.636^{***}
	(0.490)	(0.529)	(0.504)	(0.545)	(0.496)	(0.562)
Macro Signals Available$_t$		-0.311^{**}	-0.428^{***}		2.569^{*}	2.100
		(0.153)	(0.159)		(1.428)	(1.418)
Macro Signals Available$_t$ × $\mathbb{1}\{\text{Contests Experienced}_{i,t} = 2\}$			0.478			0.722
			(0.717)			(0.682)
Macro Signals Available$_t$ × $\mathbb{1}\{\text{Contests Experienced}_{i,t} = 3\}$			2.973^{***}			2.801^{***}
			(0.809)			(0.943)
Macro Signals Available$_t$ × $\mathbb{1}\{\text{Contests Experienced}_{i,t} = 4\}$			2.221^{***}			1.756^{***}
			(0.714)			(0.643)
Log Contestants$_t$				-1.311^{***}	-1.448^{***}	-1.463^{***}
				(0.143)	(0.175)	(0.176)
Macro Signals Available$_t$ × Log Contestants$_t$					-0.431	-0.357
					(0.307)	(0.305)
N	830	830	830	830	830	830
R^2	0.050	0.055	0.067	0.180	0.196	0.207

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

H.2 Official Scores

This appendix repeats key results based on contestants' out-of-sample Sharpe Ratios as dependent variables and instead uses the official scores assigned by the Quantiacs platform:

- Table IA.12 modifies the specification of Table 6 in the main paper.
- Table IA.13 modifies the specification of Table 7 in the main paper..

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

Table IA.12: Benefiting from macro data availability, and its interaction with experience. 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 best official score over the Sharpe Ratio of the benchmark index during the matched time period, which effectively controls for time periods/contests. In all specifications, the indicator "Macro Signals Available$_t$" indicates whether the contestant is a member of the Treatment group, defined in Section 5.1, or the Control group.

	Dependent variable:					
	$\text{Score}_{i,t}^{Best}$			$\text{Score}_{i,t}^{Best} - \text{Benchmark SR}_t$		
	(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	0.061	0.068	0.072	0.065	0.080	0.097

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

Table IA.13: Ruling Out Selection Effects. 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		$\text{Score}_{i,t}^{Best}$	$\text{Score}_{i,t}^{Best}$	$\text{Score}_{i,t}^{Best}$
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	0.09	0.09	0.04
	Num. obs.	1482	482	1000
	Censored	621	163	458
	Observed	861	319	542

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

I Stock Characteristics Used to Construct Predictive Signals

Table IA.14 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.14: 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.14: 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.14: 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.14: 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.14: 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.14: 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.14: 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.14: 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	Defate 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.14: 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.14: 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 monthin 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 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.14: 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 winsoriz 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.14: 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. PriceDelay Rsq = 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 reseach 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.	Gou, Lev and Shi (2006)

Table IA.14: 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 quntile 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.14: 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.14: 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)

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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. Keep only	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.14: 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)

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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)

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